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Going the distance? A meta-analysis of the deterring effect of distance in tourism

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Going the distance?—A meta-analysis of the deterring effect of distance in tourism*

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Abstract

This meta-analysis summarizes and explains the variation in the deterring effect of distance on tourism flows by analyzing 870 estimates from 139 primary studies utilizing data covering the last 25 years. We find substantial heterogeneity among studies that mostly correlates with (unobserved) study characteristics, estimation methods, and locations of origin and destination. We confirm previous findings that the mean total distance-decay effect, using preferred methods and datastructures, is close to a unit elasticity in absolute value (-0.99). However, when controlling for mediator variables, we find that the direct, physical, distance-decay effect is significantly lower (-0.83). This distance-decay effect is remarkably stable over the last 25 years and reveals a positive relation between distance and the total amount of tourists.

Keywords: meta-analysis, distance-decay, tourism flows, gravity models
JEL codes: R11, Z32

*Data and code is available upon request and will be uploaded to GitHub later. Corresponding author: Thomas de Graaff. Email: t.de.graaff@vu.nl.

I don't look down on tourism. I live in Hawaii where we have 7 million visitors a year. If they weren't there, there would be no economy. So I understand why a tourist economy is necessary.

Paul Theroux
USA Today Travel

1. Introduction

Tourists are highly unequally distributed over space. Why is it that remote island destinations such as Hawaii (Dropsy et al., 2020), Sri Lanka (Samarathunga, 2020) and Mallorca (Font, 2000) seem to defy Tobler's first Law of Geography (Tobler, 1970) and attract huge numbers of tourists traveling large distances? Or, as the juxtaposition of this, why are there large numbers of tourists traveling only small distances between neighboring countries such as the US and Mexico (32% of total visitors to Mexico is American), Germany and the Netherlands (40% of total visitors to the Netherlands is German), and Argentina and Brazil (41% of total visitors to Brazil is Argentine) (OECD, 2022)? These observations raise questions about the external validity of the impact of distance on tourism. Are there spatial and temporal contextual differences in the distance-decay component? And do cultural and natural amenities in destinations and push factors in origins affect the impact of distance? Or, has the impact of distance recently declined due to the advent of lower costs of transportation and communication? Regardless of these questions four out of five tourists still travel within their own continent (World Tourism Organization, 2018). Consequently, the decreasing costs of transportation and communication notwithstanding, the role played by distance in tourist movements appears to be still important, although its persistence and external validity are to be questioned.

To assess the persistence and external validity of the distance-decay effect in tourism, we therefore perform a meta-analysis to summarize and explain the variation in the deterring effect of distance on tourism flows by analyzing 870 estimates from 139 primary studies utilizing data covering the last 25 years. We have three main reasons to look into the deterring effect of distance on tourism flows. First, international tourism plays a large and increasing role in the world economy. Before the COVID-19 pandemic tourism directly contributed 4.4% to gross domestic product and 6.9% to total employment (OECD, 2022).[1] Note, though, that these figures can be much higher for specific countries (OECD, 2022, shows, e.g., that for Mexico tourism contributed 8% to gross domestic product while for Spain this percentage already reached 12.4% in 2019). And the precise size of the distance-decay effect itself is an important factor in predicting both bilateral and aggregate tourism flows, and as a consequence their impact on the economic and environmental performance of the receiving region. More specifically, gravity models are at the heart of the recently emerging quantitative spatial equilibrium models where calibration of the distance-decay effect plays a pivotal role (see for a recent application in tourism Faber and Gaubert, 2019).

Second, as the effect of distance seems to be heterogeneous over space, it is therefore important for local policy makers to understand how specific characteristics of both origins and destinations drive the impact of distance with respect to tourism flows. Specifically, this paper assesses to what extent distance is a composite of other less tangible factors as argued by De Groot et al. (2004) in the case of bilateral trade. If that effect is sizable, then for a specific origin-destination pair the effect of other (institutional) factors should be taken into account as well to arrive at a correct prediction.

Third, and finally, the deterring effect of distance may change over time. Particularly, it has recently been argued that the deterring effect should have decreased over recent decades, due for a large part to the advent of information and communication technology (Rosselló-Nadal and Santana-Gallego, 2024). So, the world should have become flatter. And consequently, tourists are expected to travel over larger distances—*ceteris paribus*—with possibly strong environmental consequences.

Our main findings can be summarized as follows. To start with, even though we find substantial heterogeneity among studies that mostly correlates with (unobserved) study characteristics, estimation methods, and locations of origin and destination, the preferred mean distance-decay effect (-0.99) is remarkably consistent across specifications. However, we argue that this is a total effect as we find that, controlling for mediator variables, the direct, physical, effect between distance and tourism flows is substantially lower

[1] These numbers are neither very precise nor stable across studies. For instance, Weissenberg and Langford (2018) state that the travel and tourism industry contributed about 10% to the global 2017 GDP providing some 300 million jobs corresponding to one in ten jobs. In spite of this variation, all studies signify that tourism is a large and growing sector in the world economy.

(-0.83). This indicates that a wide range of mediator variables is significantly associated with the total effect of distance, such as adjacency, world heritage sites, exchange rates and island destinations and that incorporating these mediator variables in primary studies flatten or steepen the distance-decay parameter. Furthermore, we do not find changes in the distance-decay effect over the last 25 years, neither for international nor for domestic tourism, where distance-decay effects for the latter two are remarkably similar as well. Finally, these findings combined still imply a positive relation between distance and *total* amount of tourists. We argue that this is partly due to the specification of distance-decay most often chosen in the empirical tourism flow literature: namely, a power-law.

Although we are the first to present a meta-analysis on the distance-decay effect in tourism, our study is closely related to three other studies. First, in spirit our study resembles the meta-analysis on the distance-decay effect in international trade by Disdier and Head (2008). In fact, our preferred mean distance-decay effect (-0.99) is very close to theirs (-0.91), while we as well find the distance-decay effect to be stable across time (similar to the findings of Linders et al., 2011, on the temporal stability of distance-decay effects in international trade). Second, we build upon the qualitative review of Rosselló-Nadal and Santana-Gallego (2022) on the use of gravity models in tourism. We, again, confirm their finding that the mean distance-decay effect is close to minus 1 and stable across time. Third, our quantitative meta-analytic methods are similar to those of Donovan et al. (2024) and address the large heterogeneity in empirical tourism studies, especially considering econometric methods, empirical specifications and type of and variation in origins and destinations studied. Specifically, we adopt a Bayesian multilevel approach which allows us to control for (*i*) study specific effects, (*ii*) measurement error caused by uncertainty related to the estimated precision of the sampled distance-decay effects, and (*iii*) the large variation between sampled observations themselves resulting in relatively many extreme values.[2]

The remainder of the paper is structured as follows. Section 2 presents our methodological approach. Here, we first present a microeconomic model for tourism behavior as a theoretical foundation for the use of the gravity model for tourist flows. Subsequently, subsection 2.2 discusses the specification of the distance-decay function and possible moderator and mediator variables that might affect the deterring effect of distance. Thereafter, we present meta-analysis as a research tool, report our sampling procedure, provide descriptive statistics and, finally, we motivate our specific choice for the meta-

[2]See for an early motivation for the use of Bayesian multilevel models for meta-analysis Gelman et al. (1995).

regression method, viz. a Bayesian multilevel model. Section 3 estimates our preferred specification models and presents the results, including a discussion on correcting for possible publication bias. Section 4 provides a discussion on the main findings and the last section concludes.

2. Methodology

To explain and predict bilateral tourism flows, the gravity model can be seen as a workhorse model that is most commonly used as it provides good fits to data and is well capable to explain and predict bilateral tourism flows (UNCTAD, 2012). One of the main advantages of the gravity model is given by its ability to explain tourism flows by including (*i*) demand factors, i.e. origin-related variables such as income or relative prices, (*ii*) supply factors, i.e. destination-related variables including, for instance, endowments of cultural heritage or accessibility, and (*iii*) bilateral variables such as distance between origin and destination or sharing of a common language (Park and Jang, 2014). This way, the literature shifted from focusing on demand factors only, or push factors, to the inclusion of supply elements, or pull factors, which endow destinations with the unique features that characterize them and make them attractive for tourists (Marrocu and Paci, 2013). As such, the most basic form of the model, including origin and destination Gross Domestic Products (GDPs) or origin and destination populations—corresponding to origin and destination masses—and their bilateral geographical distance, has been enriched by the literature with other relevant push and pull factors.

As per the origin-related characteristics, i.e. factors that push people to travel, level of income or GDP, population or population density and relative prices are among the most used explanatory variables. As per the destination-related features that attract tourists, an extensive number of factors has been considered including level of income or GDP, population or population density, transportation infrastructures, natural or cultural endowments, sanitary conditions, criminality rates, touristic infrastructures, and so forth. The bilateral variables are measuring dyadic relations between origin and destination, and the most frequently used are distance, common language, common border, common religion and exchange rates (for an extensive overview of the typical co-variates of gravity models applied to tourism flows see, e.g., Witt and Witt, 1995; Crouch, 1995; Lim, 1997; Rosselló-Nadal and Santana-Gallego, 2022).

The application of extended versions of the gravity model allowed the inclusion of different specific explanatory factors of interest and consequently the expression of policy recommendations on diverse topics. As a result, there is a vast heterogeneity in the empirical literature focusing on explaining tourism flows by a variety of determinants through the application of the gravity model. The main goal of such analyses varies widely across studies: on the one hand many studies investigate the determinants of tourism flows in general terms, on the other hand several articles focus on specific factors of interest in order to investigate whether or not they have an impact on tourism movements. Just to mention a few, Yang et al. (2010) focus on the role played by cultural heritage sites on tourism flows; Fourie and Santana-Gallego (2011) look at the relevance of mega-sport events in movement of tourists; Gil-Pareja et al. (2007) target the presence of embassies and consulates in the destination countries as a pull factor for tourism. Another source of heterogeneity lies in the interest in explaining domestic tourism flows (see, e.g., Marrocu and Paci, 2013; Patuelli et al., 2013), therefore focusing on a single country, or international tourism flows (see, e.g., Culiuc, 2014; Eilat and Einav, 2004). Among the ones that study international tourism flows, multiple origins and multiple destinations models can be found (see, e.g., Culiuc, 2014) in contrast with multiple origins and single destination models (see, e.g., Keum, 2010). Another important difference across primary studies is related to the adopted estimation technique including an extensive list such as pooled ordinary least squares (Yang et al., 2010), fixed effects (Gani and Clemes, 2017), random effects (Keum, 2010), generalized method of moments (Adeola and Evans, 2020), Poisson pseudo maximum likelihood (Matsuura and Saito, 2022), negative binomial models (Yang et al., 2019), and Bayesian multilevel models (Panzera et al., 2021). Finally, countries located in different parts of the world have been included in the extant literature as well as different time periods.

2.1. A structural gravity model for tourism

Despite its extensive use, the gravity model has been criticized throughout the years for lacking a solid theoretical underpinning. Bergstrand (1985), Deardorff (1998) and Anderson and Van Wincoop (2003), among others, successfully introduced a theoretical basis for applications of the model to trade flows and Morley et al. (2014) were one of the first to provide a theoretical foundation for the application of the gravity model to tourist flows showing its link with individual utility theory—citing Morley et al. (2014): "Gravity models recently applied in the literature can be understood as the exploration of the spatial dimension of the theoretical tourism demand function". More recently, Faber and Gaubert (2019) developed a microeconomic framework to estimate a quantitative spatial equilibrium model to estimate the effects of tourism flows to Mexico.

As further microeconomic foundations of tourists' choices are relatively scarce, we adopt modeling strategies from the urban and regional economic literature to derive a preferred specification for the gravity model (see Morley et al. (2014) and Santana-Gallego and Paniagua (2022) for alternative approaches). Specifically, we follow the market-clearing approach of Anderson (2011) combined with the utility specification of recent quantitative spatial equilibrium models (most notably Ahlfeldt et al. (2015) and Faber and Gaubert (2019)).

To start, consider a representative consumer i living in region o ($o \in \{1, \dots, R\}$) who has an endowment of a fixed amount of leisure time for maximal one trip per year, which the consumer spends in region d ($d \in \{1, \dots, R\}$) thus choosing between R regions including home region o. The consumer derives utility by consuming two types of goods, a (Hicksian) composite commodity c to be consumed in o and spending leisure time l in a destination d as follows (see the seminal paper of Ahlfeldt et al., 2015, for an application to commuting):

$$U_{iod} = z_{iod} \left(\frac{c_{io}}{\beta} \right)^{\beta} \left(\frac{B_d l_{id}}{1 - \beta} \right)^{1-\beta}, \tag{1}$$

where z_{iod} denotes the idiosyncratic preferences of consumer i living in origin o and traveling to destination d and B_d is the general utility of being in destination d (a destination specific amenity level). Normalizing the price for the commodity c, the consumer faces the following budget constraint:[3]

$$Y_o = p_d \tau_{od} l_{id} + c_{io}, \tag{2}$$

where Y_o is homogeneous income earned in origin o, p_d the average price level for spending leisure time in d, and τ_{od} are friction costs to travel from o to d. Note that, if consumer i decides to spend leisure time in his or her own region (so $d = o$), τ_{oo} should

[3] If we relax the assumption of fixed amount of leisure time, then there will be a trade-off in time between working hours (h) and leisure time (l), for which we then need an additional time constraint, namely $T_i = h_i + l_i$ with T_i denoting individual i's total time endowment. Combining this with the monetary constraint $Y_o = \omega_o h_i = p_d \tau_{od} l_{id} + c_{io}$ yields the combined constraint: $\omega_o T_i = (p_d \tau_{od} + \omega_o) l_{id} + c_{io}$ with ω_o the wage rate in o. So, there is an additional opportunity cost of spending leisure time priced at wage rate ω_o. Though perhaps more realistic, this yields an additive structure in both the indirect utility function and the final gravity model. For clarity reasons and to stay as close as possible to the empirical literature, we therefore keep the assumption of a fixed amount of leisure time.

be equal to one as income should not diminished by friction or travel costs between o and d. Indirect utility can then be readily derived as:

$$u_{iod} = z_{iod} Y_o \left(\frac{B_d}{\tau_{od} p_d} \right)^{1-\beta}. \tag{3}$$

Conform to Faber and Gaubert (2019) we assume that the idiosyncratic preferences z_{iod} are Fréchet distributed with mean 1 and shape parameter ϵ (with $\epsilon > 0$), so $F(z_{iod}) = \exp(-z_{iod}^{-\epsilon})$. The lower parameter ϵ is, the *more* consumers are heterogeneous in their traveling preferences. Integrating over z_{iod} yields the probability, π_{od}, that someone who is living in origin o decides to travel to d:[4]

$$\pi_{od} = \frac{(\tau_{od} p_d)^{-(1-\beta)\epsilon} B_d^{(1-\beta)\epsilon} Y_o^{\epsilon}}{\sum_{r=1}^{R} \sum_{s=1}^{R} (\tau_{rs} p_s)^{-(1-\beta)\epsilon} B_s^{(1-\beta)\epsilon} Y_r^{\epsilon}}. \tag{4}$$

As we assume that the consumer faces only the choice of a tourist destination, Equation (4) simplifies to the following probability to travel to d conditional on living in o:

$$\pi_{od|o} = \frac{(\tau_{od} p_d)^{-(1-\beta)\epsilon} B_d^{(1-\beta)\epsilon} Y_o^{\epsilon}}{\sum_{s=1}^{R} (\tau_{os} p_s)^{-(1-\beta)\epsilon} B_s^{(1-\beta)\epsilon} Y_o^{\epsilon}} = \frac{(\tau_{od} p_d)^{-(1-\beta)\epsilon} B_d^{(1-\beta)\epsilon}}{\sum_{s=1}^{R} (\tau_{os} p_s)^{-(1-\beta)\epsilon} B_s^{(1-\beta)\epsilon}}, \tag{5}$$

so canceling out income in origin o and yielding the micro-foundations for structural-form gravity equations.

Market clearing conditions impose that total amount of tourists traveling to destination d, N_d, should be the sum of tourists from all regions o, T_{od}, into d (see, e.g. Anderson, 2011; Santana-Gallego and Paniagua, 2022). Thus:

$$N_d = \sum_o T_{od} = \sum_o \pi_{od|o} N_o = \sum_o \frac{(\tau_{od} p_d)^{-(1-\beta)\epsilon} B_d^{(1-\beta)\epsilon}}{\sum_{s=1}^{R} (\tau_{os} p_s)^{-(1-\beta)\epsilon} B_s^{(1-\beta)\epsilon}} N_o, \tag{6}$$

where N_o denotes the total amount of consumers traveling from o.

Now, define the total outward tourist market potential from o as the denominator in Equation (5), so $O_o \equiv \sum_{s=1}^{R} (\tau_{os} p_s)^{-(1-\beta)\epsilon} B_s^{(1-\beta)\epsilon}$, then, the tourist market clearing

[4] Fréchet distributions are increasingly used in regional and urban economics to model idiosyncratic preferences with as main advantage that they can be used in a multiplicative way. As Extreme Value Type II distributions, Fréchets distributions are closely related to Extreme Value Type I distributions (Gumbel distributions), where a logarithmic transformation of the Fréchet distribution can be mold into a Gumbel distribution. For details we refer to Eaton and Kortum (2002) and Ahlfeldt et al. (2015). See as well Fosgerau and Bierlaire (2009) for an alternative approach to multiplicative errors.

condition becomes:

$$N_d = B_d^{(1-\beta)\epsilon} p_d^{-(1-\beta)\epsilon} \sum_o \frac{\tau_{od}^{-(1-\beta)\epsilon}}{O_o} N_o. \tag{7}$$

So, every tourist travels to some region d—possibly similar to the origin o. Isolating $B_d^{(1-\beta)\epsilon}$ in Equation (7) yields:

$$B_d^{(1-\beta)\epsilon} = \left(\frac{N_d}{D_d N}\right), \tag{8}$$

where

$$D_d \equiv p_d^{-(1-\beta)\epsilon} \sum_o \frac{\tau_{od}^{-(1-\beta)\epsilon}}{O_o} \frac{N_o}{N}. \tag{9}$$

Now, using Equation (8) and substituting for the destination's amenity level B_s in O_o yields:

$$O_o = \sum_s \frac{(\tau_{os} p_s)^{-(1-\beta)\epsilon}}{D_s} \frac{N_s}{N}, \tag{10}$$

and substituting the equation for amenities (8) and using Equation (7) leaves us with a structural gravity model of tourism:

$$T_{od} = \frac{N_o N_d}{N} \frac{(\tau_{od} p_d)^{-(1-\beta)\epsilon}}{O_o D_d}. \tag{11}$$

To mold the gravity model in a linear regression form, often equation (11) is log-linearized, yielding the following reduced form:

$$\ln(T_{od}) = C + \nu_o + \iota_d + \beta_1 \ln(N_o) + \beta_2 \ln(N_d) + \beta_3 \ln(p_d) + \beta_4 \ln(\tau_{od}), \tag{12}$$

where C denotes a constant that includes the effect of total tourists N, ν_o and ι_d are generic origin and destination specific effects capturing O_o and D_d, and β_1–β_4 are parameters to be estimated—where β_1 and β_2 should theoretically be close to 1 and both β_3 and β_4 should be equal to $-(1-\beta)\epsilon$. Thus, the deterring effect of distance on tourism is stronger if the share of income spend on leisure time increases ($1-\beta$ increases) and if preferences for traveling destinations are more homogeneous (ϵ increases). Moreover, because Equation (12) is in a log-log form parameters β_1–β_4 denote elasticities. Finally, if ν_o and ι_d are specified as fixed effects, then β_1–β_3 are not identified unless there is variation over time. The next subsection discusses the implementation of τ_{od}.

Obviously, the micro-economic structure specified by Equations (1) and (2) is very basic but already yields useful insights. First, the variables N, N_o, and N_d are defined by the (total) number of tourists, not by the total population. So, ideally total number of tourists should be used in a gravity model, which for origins might align with population, but not for destinations. Second, just as in Anderson and Van Wincoop (2003), and inevitably, origin (O_o) and destination specific variables (D_d) emerge, pointing to the need to account explicitly for origin and destination specific effects, for example in the form of fixed or random effects. Third, the market clearing condition in Equation (7) only holds if all tourists between and within regions are taken into account. Fourth, and finally, even if Equation (2) does not directly consider tourism as a luxury good, the relative size of friction costs τ_{iod} to wages ω_{io} might rule out particular tourism flows from o to d yielding zero observations. In the next subsection we focus on the implementation of τ_{iod} in empirical tourism analyses and its consequences.

2.2. Distance-decay effects and mediator variables

Interestingly, and contrary to empirical practice, derivations based upon micro-economic utility frameworks almost always strongly suggest that the specification should be exponential (see, amongst others, Cochrane, 1975; Choukroun, 1975; Ahlfeldt et al., 2015):

$$\tau_{od} = \exp\left(-\gamma d_{od}\right), \tag{13}$$

where d_{od} denotes Euclidean distance between o and d. Indeed, Equation (2) favors an exponential function above a power-law as well because in the case of zero distance, τ_{od} should be equal to one as it should have no effect.

Following the seminal work of Tinbergen (1962), and as well often based upon better model performance, the very vast majority of studies implement power-laws[5], and we therefore focus our attention to the distance-decay function as specified as follows (14).

$$\tau_{od} = d_{od}^{-\gamma}. \tag{14}$$

Note, though, that this is not an innocuous assumption given our theoretical framework above and the fat tails usually associated with power-laws as we show further below. The structural interpretation of β_4 in reduced-form model (12) should now be $\beta_4 = -(1-\beta)\epsilon\gamma$, pointing out that the estimated distance-decay parameter in gravity models is typically a

[5] There are still many other alternative specifications (see for a discussion de Vries et al., 2009).

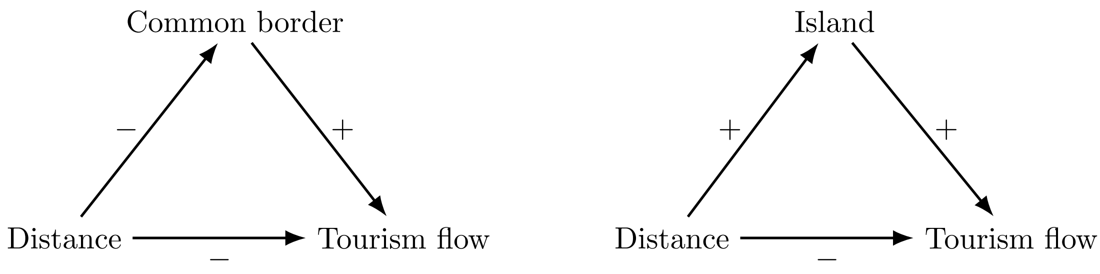

Figure 1: Impact of mediator variables that are negatively associated with distance such as having a common border (left panel) and positively associated with distance such being an island destination (right panel).

composite of multiple structural parameters.

Regardless of the specification, it is not immediately clear why the impact of distance structurally varies over and within studies. We propose three potential sources for this variation. First, estimates vary methodologically in terms of statistical methods, data structure and data selection. Second, estimates vary because of observed and unobserved contextual (time and region) specific effects.[6] Third, and finally, estimates vary because of the adoption of other (mediator) variables.

The last source of variation is more subtle than it seems on first sight. Distances (usually Euclidean distances measured in kilometers) are themselves not affected by other factors and as such can be seen as exogenous. However, distance is associated with other variables. To illustrate this, consider the diagrams in Figure 1. The left panel depicts a negative correlation between distance and having a common border. That is, countries with common borders are usually close to each other. Common borders also have a positive impact on international tourism flows via different channels than distance; channels which are usually associated with trust and familiarity. Therefore, we posit that distance has a direct negative effect on tourism flows and on top of that a negative indirect effect as well via having a common border. The right panel depicts an opposite indirect effect. Here, there is a positive relation between distance and islands as islands are, ceteris paribus, relatively remotely located. But islands themselves—due to natural amenities—often act as pull factors for tourists, so that the indirect effect of distance here is positive.

[6]For example, because of its geographical location, tourists need to travel over larger distances to New Zealand than to comparable destinations.

To illustrate this further, we simulate data from the relations in both diagrams in Figure 1 and regress tourism flows on distance with and without inclusion of the additional mediator variable. Figure 2 shows the resulting scatter plots and regression lines. In line with Figure 1 the left scatter plot shows that controlling for a border effect yields a flatter distance-decay curve. On the contrary, the right scatter plot yields steeper distance-decay curves when controlling for island destinations. In both panels the red lines denote the direct effect and the blue lines the total effect of distance. Thus, mediator variables having a positive effect on tourism and negatively associated with distance yield negative estimates of the mediator variables and flatten the direct effect of distance. Mediator variables having a positive effect on tourism and positively associated with distance result in positive coefficients of the mediator variables and steepen the direct effect of distance.

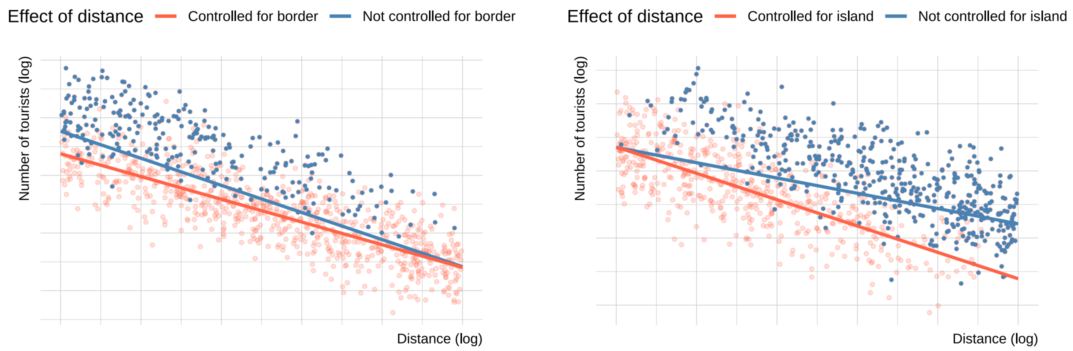

Figure 2: Simulation of distance-decay effects when or not controlled for border effects (left panel) and island effects (right panel). For both panels the blue line denotes the total effect of distance on tourist flows and the red line the direct effect of distance on tourist flows. Blue points denote observations where the common border variable equals one (left panel) or the island variable equals one (right panel).

2.3. Systematic review

To understand the determinants of the heterogeneity of the distance decay effect on tourism flows across primary estimates, we apply a meta-analysis to the existing literature. Specifically, we define our effect size as the estimated distance decay effect or the (theoretically negative) elasticity between distance and tourism flows—denoted by β_4 in equation (12) and expecting β_4 to be negative. Although meta-analysis is already often applied within the tourism literature at large—a non-exhaustive list of examples include meta-analyses on tourism demand (Crouch, 1995), on tourism and GDP (Castro-Nuño et al., 2013), on tourism demand elasticities (Peng et al., 2015), on the effect of UNESCO World Heritage sites on tourism (Yang et al., 2019), and on the effect of tourism development on poverty alleviation (Zhang et al., 2023)—there is yet no quantitative systematic review on the role of distance in tourism flows, which is remarkable because, as Rosselló-Nadal and Santana-Gallego (2022) clearly show, there is a large body of empirical studies utilizing gravity models to explain the size of tourism flows. And most of them include distance as a key determinant of tourism flows.

As Stanley and Doucouliagos (2012) argue, meta-analysis is a research method used to systematically review research findings using statistical techniques to summarize in a statistically rigorous way the results obtained by the literature on a specific topic. An important advantage gained by using meta-analysis as an instrument for literature review is given by the possibility to statistically examine differences in primary studies' characteristics—such as methods, data, time spans, specifications, and as such assess the way in which they affect the research results (Stanley, 2001). Comparing a meta-analysis to a qualitative literature review, the former is more objective and allows to investigate the causes of quantitative variation in the primary estimates (Florax et al., 2002). As Glass (1976) argues, meta-analysis "refers to the analysis of analyses", or—somewhat more nuanced—citing from Sutton et al. (2000): "By bringing together the results of research in a systematic way, appraising its quality in the light of the question being asked, synthesizing the results in an explicit way and making this knowledge base more accessible, it is hoped to foster greater sensitivity to the evidence by researchers, policy makers, practitioners and the public."

Figure 3 depicts our systematic search. We start our systematic review by searching online using the keywords "gravity" and "touris*", where the latter can denote various forms such as tourism and tourists.[7] Because we want to assess the impact of distance over time as well, we restrict our search only to publications since 2000, as the number of publications dated before 2000 is very low. This yields 670 studies. We then omit 564 studies for the following reasons: no explicit gravity model (usually a Geographical Information System approach instead), no empirical estimates, no standard errors (or related information on precision)[8], no distance coefficient (recent studies often adopt pair-wise fixed effects removing dyadic time-invariant variables such as distance), no regional variation (only

[7]The search was undertaken on January 20th, 2025, using the Internet database Scopus.

[8]Some studies only provide information on p-values via significance levels. If so, we impute standard errors taking the mean probability of the indicated left and right tails.

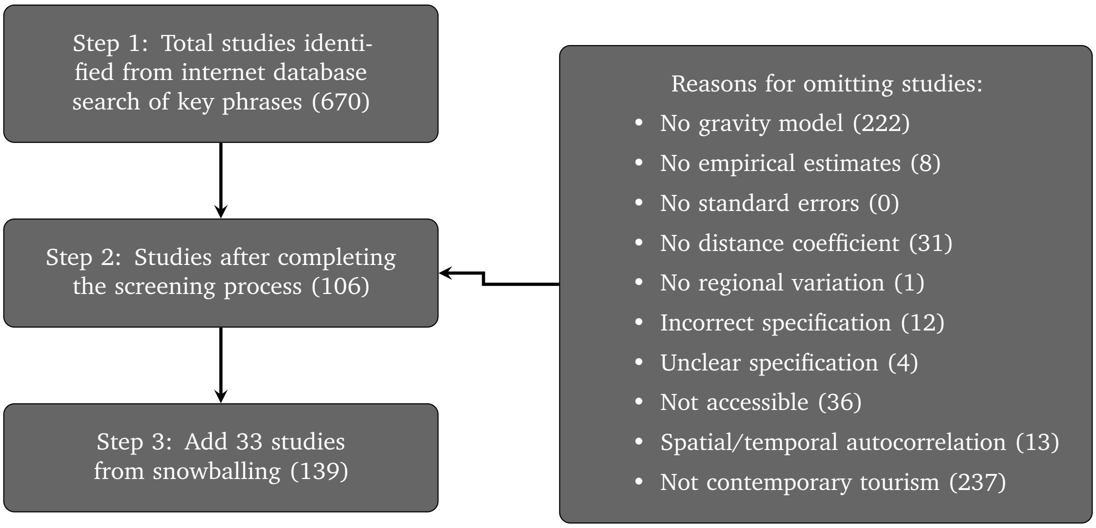

Figure 3: Flow of study selection in the systematic review (adapted from Moher et al., 2009)

applies if both origin and destination yields little spatial variation), study with unclear specification, study is not accessible, if the specification contains spatial or temporal autocorrelation (prohibiting direct comparisons of the effect size), and finally not about contemporary tourism at all (there is a surprisingly large literature about space tourism). Note, that reasons for omission are not mutually exclusive. This procedure yields 106 studies. In the final step we add 33 studies from snowballing (usually from previous overview studies, such as Castro-Nuño et al., 2013; Yang et al., 2019; Rosselló-Nadal and Santana-Gallego, 2022). In the end, our sample consists of 870 estimates from 139 primary studies.

2.4. Data description

Summarizing the effect sizes by visually analyzing their underlying distribution and heterogeneity represents an insightful instrument both to visualize the data and to choose the appropriate meta-regression specification. Therefore, in the left panel of Figure 4 the distance elasticity of tourism demand is plotted against the frequency to investigate the underlying distribution of the data and the overlay of a normal distribution curve is indicated as well to assess heterogeneity and divergence from normality (Bax et al., 2009). As the histogram clearly does not represent a perfect normal distribution, we infer that a sizable extent of heterogeneity is present in the estimated effect sizes, which at first sight cannot be explained by sampling error (Linders et al., 2011).

The right panel of Figure 4 plots the estimated distance coefficients, which allows us to visualize all effect sizes combined and to detect the heterogeneity among the results throughout the primary studies. The estimations are ordered according to their size and the vertical and horizontal dashed lines indicate the mean of the effect sizes (-1.09) accompanied by one standard deviation on both sides indicated by dotted lines. As evident from the graph, the estimates appear to be quite heterogeneous, partly confirmed by the non-inclusion of the mean value in most of the single estimates' confidence intervals. Thus, we infer that the large detected heterogeneity in effect sizes is to a large extent due to each primary study's specific characteristics.

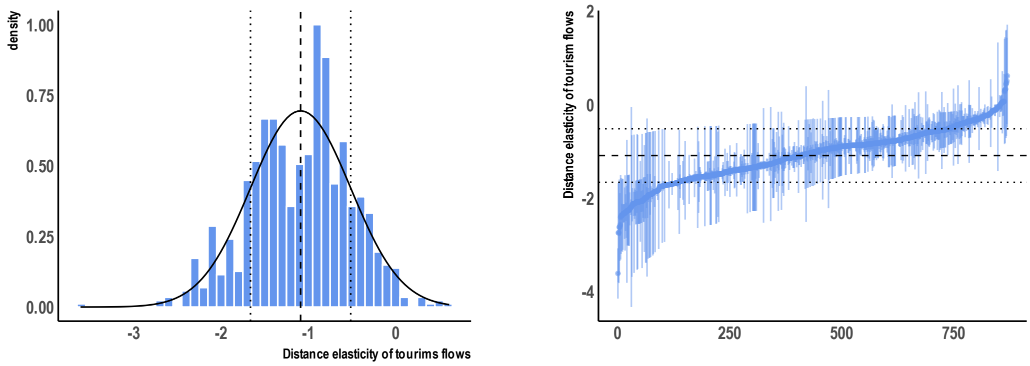

Figure 4: Histogram with corresponding Normal distribution (left panel) and distribution in combination with standard errors of effect sizes (right panel). Dashed lines indicate the mean of the sample (-1.09) and dotted lines the standard deviations on both sides.

As explained in Subsection 2.2, we argue that the effect size may vary systematically because of (*i*) (methodological) differences in statistical methods, data structure and data selection, because of *ii*) observed and unobserved contextual (both temporal and spatial) effects, and (*iii*) because of the use of various mediator variables. To assess the size of this systematic variation we sample additional data from the primary studies to control for in our meta-analysis. To start with, Table 1 shows the controls dealing with the methods and methodology variables—all being indicator or dummy variables—we sample for our meta-regression model together with a brief description and their means.

Table 1: Meta-regression model: method and methodology controls

Name	**Description**	**Mean**
PPML	Dummy variable taking the value of 1 if PPML is used; 0 otherwise	0.23

Continued on next page

Table 1—continued from previous page

Name	**Description**	**Mean**
Least squares	Dummy variable taking the value of 1 is a type of least squares are used; 0 otherwise	0.64
Max. likelihood	Dummy variable taking the value of 1 if maximum likelihood is used; 0 otherwise	0.09
Neg. binomial	Dummy variable taking the value of 1 if negative binomial estimation is used; 0 otherwise	0.03
Other	Dummy variable taking the value of 1 if a different estimation method is used; 0 otherwise	0.01
Zero inflated	Dummy variable taking the value of 1 if controlled for excessive zeros; 0 otherwise	0.02
Fixed effects	Dummy variable taking the value of 1 if fixed effects are used; 0 otherwise	0.51
Random effects	Dummy variable taking the value of 1 if random effects are used; 0 otherwise	0.12
Panel	Dummy variable taking the value of 1 if panel data; 0 otherwise	0.86
Arrivals	Dummy variable taking the value of 1 if dependent variable measures arrivals; 0 otherwise where it measures overnight stays	0.96
Origin constrained	Dummy variable taking the value of 1 if no variation in origin; 0 otherwise	0.04
Destination constrained	Dummy variable taking the value of 1 if no variation in destination; 0 otherwise	0.35
Imputed s.e.	Dummy variable taking the value of 1 if standard errors are imputed; 0 otherwise	0.12

First, we record the estimation method. Since the seminal work of Silva and Tenreyro (2006) most empirical gravity models (especially in trade studies) are estimated with the Poisson pseudo-maximum likelihood (PPML) estimator as it tackles both zeros and heteroskedasticity on the one hand and can deal with large datasets and the use of fixed effects on the other hand. In tourism studies, however, various types of Least Squares estimators (sometimes dealing with endogeneity using 2 Stage Least Squares estimators) are still the most prevalent. Negative binomial, zero inflated and other estimators (such as Bayesian multilevel models) are much less often used. Moreover, as Equation (12) shows it is important to control for origin and destination specific effects. Almost half of the studies do so by applying fixed effects. Random effects are much less applied. In terms of data we observe whether there is time-varying (panel) data, and whether the dependent variable is arrivals or numbers of overnight stays. Moreover, we note whether data is origin constrained (so only flows from one country or region) or destination constrained. Finally, we record whether we had to impute the standard errors.

Table 2 shows the controls dealing with the contextual (both regional and temporal) variables we sample for our meta-regression model.

Table 2: Meta-regression model: contextual controls

Name	Description	Mean
Origin intercontinental	Dummy variable taking the value of 1 if intercontinental origin; 0 otherwise	0.79
Origin continental	Dummy variable taking the value of 1 if continental origin; 0 otherwise	0.07
Origin national	Dummy variable taking the value of 1 if country origin; 0 otherwise	0.14
Origin Europe	Dummy variable taking the value of 1 if origin includes Europe; 0 otherwise	0.86
Origin Australia	Dummy variable taking the value of 1 if origin includes Australia; 0 otherwise	0.69
Origin Africa	Dummy variable taking the value of 1 if origin includes Africa; 0 otherwise	0.56
Origin North America	Dummy variable taking the value of 1 if origin includes North America; 0 otherwise	0.74
Origin South America	Dummy variable taking the value of 1 if origin includes South America; 0 otherwise	0.53
Origin Asia	Dummy variable taking the value of 1 if origin includes Asia; 0 otherwise	0.83
Destination intercontinental	Dummy variable taking the value of 1 if intercontinental destination; 0 otherwise	0.44
Destination continental	Dummy variable taking the value of 1 if continental destination; 0 otherwise	0.10
Destination national	Dummy variable taking the value of 1 if country destination; 0 otherwise	0.46
Destination Europe	Dummy variable taking the value of 1 if destination includes Europe; 0 otherwise	0.56
Destination Australia	Dummy variable taking the value of 1 if destination includes Australia; 0 otherwise	0.44
Destination Africa	Dummy variable taking the value of 1 if destination includes Africa; 0 otherwise	0.42
Destination North America	Dummy variable taking the value of 1 if destination includes North America; 0 otherwise	0.45
Destination South America	Dummy variable taking the value of 1 if destination includes South America; 0 otherwise	0.42
Destination Asia	Dummy variable taking the value of 1 if destination includes Asia; 0 otherwise	0.71
Publication year	Year of publication of primary study	2018
Average year	Average year of data used by primary study	2007

As the size of the distance-decay effect may vary over space, we sample two types of regional variables. First, for both origins and destinations we note whether data variation is over continents, within continents or within country (i.e., over regions). Second, we register as well both for origins and destinations the region of the data (in terms of continents), where a 1 indicates that at least one country from that region is included in the sample (as origin and destination, respectively). Notably, most flows are intercontinental, coming from North-America and Europe and going to Asia. The latter is explained by the large amount of studies dealing with tourism flows into China. To allow for temporal analyses we sample as well the year of publication and the (average) year of the data used.

Finally, Table 3 shows the mediator variables we sample for our meta-regression model. We justify the choice for these variables by the qualitative overview of variables used given in Table 4 on page 1372 by Rosselló-Nadal and Santana-Gallego (2022). We aim here to be as complete as possible to avoid possible omitted variable bias. Note that, for interpretation reasons and to be able to make a distinction between total and direct effects in our specification (see Figures 1 and 2) we define all variables in Table 3 as indicator variables with value 1 if *not* incorporated in the primary study.

Table 3: Meta-regression model: mediator variables

Name	**Description**	**Mean**
GDP origin	Dummy variable taking the value of 1 if GDP of origin is **not** included	0.65
GDP per capita origin	Dummy variable taking the value of 1 if GDP per capita of origin is **not** included	0.46
Population origin	Dummy variable taking the value of 1 if population of origin is **not** included	0.34
GDP destination	Dummy variable taking the value of 1 if GDP of destination is **not** included	0.79
GDP per capita destination	Dummy variable taking the value of 1 if GDP per capita of destination is **not** included	0.59
Population destination	Dummy variable taking the value of 1 if population of destination is **not** included	0.56
Colony	Dummy variable taking the value of 1 if colony variable is **not** included	0.54
Language	Dummy variable taking the value of 1 if language variable is **not** included	0.39
Common border	Dummy variable taking the value of 1 if border variable is **not** included	0.45

Continued on next page

Table 3—continued from previous page

Name	Description	Mean
Exchange rate	Dummy variable taking the value of 1 if exchange rate variable is **not** included	0.74
Common currency	Dummy variable taking the value of 1 if common currency variable is **not** included	0.87
Regional trade agreement	Dummy variable taking the value of 1 if regional trade agreement variable is **not** included	0.80
Price ratio	Dummy variable taking the value of 1 if price ratio variable is **not** included	0.60
World heritage site	Dummy variable taking the value of 1 if destination has **no** world heritage sites	0.90
Island	Dummy variable taking the value of 1 if destination is **not** an island	0.77
Climate	Dummy variable taking the value of 1 if climate variables are **not** controlled for in destination	0.89
Sea	Dummy variable taking the value of 1 if destination has **no** sea access	0.81
Politics	Dummy variable taking the value of 1 if political variables are **not** controlled for	0.85
Culture	Dummy variable taking the value of 1 if cultural variables are **not** controlled for	0.80
Religion	Dummy variable taking the value of 1 if religious variables are **not** controlled for	0.88
Trade	Dummy variable taking the value of 1 if **not** controlled for trade between origin and destination	0.86
Migration	Dummy variable taking the value of 1 if **not** controlled for migration between origin and destination	0.98
Disease	Dummy variable taking the value of 1 if **not** controlled for diseases in destination	0.90

Equation (12) states that, ideally, gravity specifications should contain total number of tourists in origin and destination and price variables in destination. However, as these variables usually do not change much over time the inclusion of fixed effects for origin and destination already controls for a large part for these variables. Moreover, even when included these variables do no necessarily impact the effect size. Other often included variables are colony, language, common border, exchange rate, common currency, regional trade agreement and price ratio. These types of variables vary over each origin-destination combination (so, for each dyadic pair). The variable trade and migration, and less so politics and culture, change as well over each dyadic pair but their endogeneity are often difficult to control for. Finally, variables as world heritage sites, island, climate, sea and disease measure the attractiveness of the destination and thus form part of the amenity variable as measured by B_d in Equation (1).

2.5. Quantitative methods

Being highly heterogeneous, as Figure 4 indicates, studies' individual effect sizes depend strongly on study specific individual effects and characteristics for which we need to control in a meta-regression analysis. For estimation, we adopt the relatively recent implementation of Bayesian multilevel models for meta-analysis in the social sciences (see, among others, Meager, 2019; Kline et al., 2019; Donovan et al., 2024, for recent applications). This offers us three main advantages over more traditional meta-regression models. First, it can address study heterogeneity by including individual group effects for each study in a mixed-effects type of approach. As such, we assume that study effects are drawn from a common distribution with unknown variance that is to be estimated. This allows for partial pooling and avoids extreme over-fitting as, e.g., fixed effects would do when facing small numbers of supporting observations. And, as Table A in the Appendix shows, the range of observations per study falls within the range 1–48, yielding relatively little variation for individual fixed study effects. Second, it is straightforward to explicitly model measurement error within a Bayesian multilevel model. And as shown in Figure 4, there is large variation in the *precision* of the effect sizes. Therefore, we assume that our *observed* effect size is a stochastic function of the *true* effect size, using the standard error of the estimates as standard deviation. Finally, to further address the heterogeneity among effect sizes we adopt a Student's t-distribution for the effect size, which, compared to the conventional normal distribution, is able to better address the outliers in our sample (*cf.* Donovan et al., 2024).

We propose four nested Bayesian multilevel meta-analysis models, ranging from simple linear to more complex models. We start with our most simple linear model in distributional form:

$$\delta \sim N(\mathbf{X}\beta, \sigma) \qquad \text{(Model A)}$$

where δ is the vector of effect sizes which we assume to be normally distributed with mean $\mathbf{X}\beta$ and standard deviation σ, where $\mathbf{X}$ denotes the constant and possibly a set of co-variates with β its associated parameters. As we estimate our models in a Bayesian way we set priors to all our parameters as follows: all co-variate parameters β have somewhat non-informative priors distributed as $N(0, 0.5)$ except for our constant which, inspired by the left panel of Figure 4, has a prior distributed as $N(-1, 1)$. Our priors for standard deviations are set at a Cauchy distribution with mean zero and standard deviation one, which yields a positive but rather flat (non-informative) distribution.

Our second model includes study specific effects as follows:

$$\begin{aligned} \delta &\sim N(\xi + \mathbf{X}\beta, \sigma) \\ \xi &\sim N(0, \sigma_\xi), \end{aligned} \tag{Model B}$$

where the vector ξ denotes study specific effects and is drawn from a normal distribution with an unknown and, thus, to be estimated standard deviation.[9] The standard deviation σ_ξ is of particular interest here as it estimates to what extent effect sizes share a similar distribution. If it tends towards zero there is complete pooling and individual study effects ξ are close to zero. If σ_ξ is very large relative to the effect size there is no pooling and ξ converge to the case of fixed effects. In between there is partial pooling, entailing in our case that studies' effect sizes are to a certain extent related to each other. In our setting, a particular advantage of this approach is we can include as well studies with just one observation. Perhaps even more importantly this partial pooling approach leads to statistical shrinkage—outliers are estimated to be closer to the mean.

Our third model takes into account that effect sizes δ are themselves measured with *known* uncertainty, as each observed distance decay parameter has an associated standard error, s_i—that is within our sample and according to our sample selection criteria.

$$\begin{aligned} \delta &\sim N(\delta^{\text{true}}, s) \\ \delta^{\text{true}} &\sim N(\xi + \mathbf{X}\beta, \sigma) \\ \xi &\sim N(0, \sigma_\xi), \end{aligned} \tag{Model C}$$

with s the vector of standard errors observed from the primary studies. Thus, Model C models observed effect sizes as distributed around an unknown mean—possibly conditional on covariates—and effectively gives less weight on those observations with larger uncertainty.

Finally, our fourth model addresses the large ("fat") tails as observed in the left panel of

[9]The overall mean study effect ends up in the general constant and constitutes our mean effect size.

Figure 4. To this end, we model our effect sizes being distributed according to a Student's t-distribution as follows:

$$\begin{aligned} \delta &\sim N(\delta^{\text{true}}, s) \\ \delta^{\text{true}} &\sim t(\xi + \mathbf{X}\beta, \sigma, \nu) \\ \xi &\sim N(0, \sigma_\xi), \end{aligned} \tag{Model D}$$

where ν denotes the degrees of freedom. For interpretation, when ν is relatively large (> 30) then the distribution converges to the normal distribution.

3. Model results

We fit Model A–Model D with the `brms` package using the statistical platform `R` and the STAN software (Bürkner, 2017a; Bürkner, 2017b; R Core Team, 2021; Carpenter et al., 2017). All models were run with 3 Markov chains each consisting of 5,000 iterations with 2,000 warm-up iterations and converged very quickly.[10]

3.1. Intercept only models

Table 4 provides the estimation results for Model A–Model D, focusing only on the implied mean effect size.[11] Notwithstanding that the effect size is very stable across all four models, both the loo-ic and model weights very clearly prefer Model D, the model with varying effects, errors in outcomes and Student's t-distribution.[12] Clearly, the mean

[10]Converge is both assessed with visual inspection of the Markov chains and by all resulting R-hats being (much) smaller than 1.05 and close to 1 (Brooks and Gelman, 1998).

[11]The implied mean effect size is the mean of the posterior predictive distribution (Bürkner, 2017b). Note that the implied mean effect size is typically not similar to the constant as *all* parameters are correlated with each other. For the simple linear model constant and implied mean effect size coincide, but this is not the case for more complex models, where the constant could, e.g., be correlated with the study varying effects.

[12]Model weights are based on loo-ic, which is the leaving-one-out (loo) information criterion (ic) calculated by efficient leave-one-out cross-validation using Pareto smoothed importance sampling based upon Vehtari et al. (2017). The smaller the loo-ic the better (out-of-sample) model performance. The R^2 here is the Bayesian equivalent of the regular R^2 and differs slightly as it also takes into account the uncertainty that is brought in by the prior distributions for the parameters (Gelman and Pardoe, 2006). With not too precise prior distributions and a reasonable amount of observations—as we arguably have—the difference between the two types of R^2s is usually rather small.

distance-decay across all studies is slightly below to -1.1, also when controlling for heterogeneity and errors-in-outcomes. There are three other observations to be made. First, Model C with varying effects and errors-in-outcomes shows that the variation between studies accounts for 77% ($= \frac{\sigma_s^2}{\sigma_s^2+\sigma^2} = \frac{0.49^2}{0.49^2+0.27^2}$) of total variation, revealing the large heterogeneity between studies. Second, the difference in loo-ic between Model B and Model C is not very large, indicating that errors-in-outcomes is not very important for this sample. Finally, the Student's t-distribution parameter ν is relatively close to one, pointing to the presence of "fat" tails, again the large heterogeneity between studies, and the possible specification error of using a Normal distribution.

Table 4: Meta-analysis regression results—intercept only models (standard errors between parentheses)

	Model A	Model B	Model C	Model D
Constant	-1.09 (0.02)***	-1.10 (0.05)***	-1.09 (0.04)***	-1.08 (0.05)***
Model parameters				
σ	0.57 (0.01)***	0.32 (0.01)***	0.27 (0.01)***	0.05 (0.01)***
σ_ξ		0.51 (0.04)***	0.49 (0.03)***	0.52 (0.03)***
ν				1.41 (0.14)***
Implied mean effect size	-1.09 (0.02)***	-1.09 (0.15)***	-1.08 (0.15)***	-1.07 (0.08)***
loo-ic	1506.60	602.80	571.80	78.00
Model weights	0.00	0.00	0.00	1.00
R^2	0.00	0.69	0.67	0.69

Notes: *p<0.1; **p<0.05; ***p<0.01. All models use 870 observations, as per Subsection 2.4

3.2. Publication bias

One of the most topical methodological issues in meta-analysis is the possible presence and influence of publication bias in primary studies (see as well Havránek et al., 2020), which occurs when the probability of a study getting published is affected by its methodological approach, methods adopted, or results (Harrer et al., 2019) and therefore creates sample selection bias in the data resulting in a non-representative sample of the total population of research findings. Figure 5 shows the possible presence of publication bias in our sample.

The left panel of Figure 5 shows the distribution of t-statistics in our sample (with a cut-off point of -20). Although there is some probability mass close to the 5% significance level (corresponding to a t-statistic of 1.96—the dotted black line), the evidence for publication bias is not overwhelming. Note that the spike is caused by the imputation of standard errors. The funnel plot in the right panel shows more convincingly that publication bias is most likely not a severe issue. Here the distribution seems symmetrical, and there does not seem to be bunching close to the 5% significance level (the dotted lines) (Harrer et al., 2019). Note again the effect of the imputation of standard errors, causing a number of observations to be on a straight line.

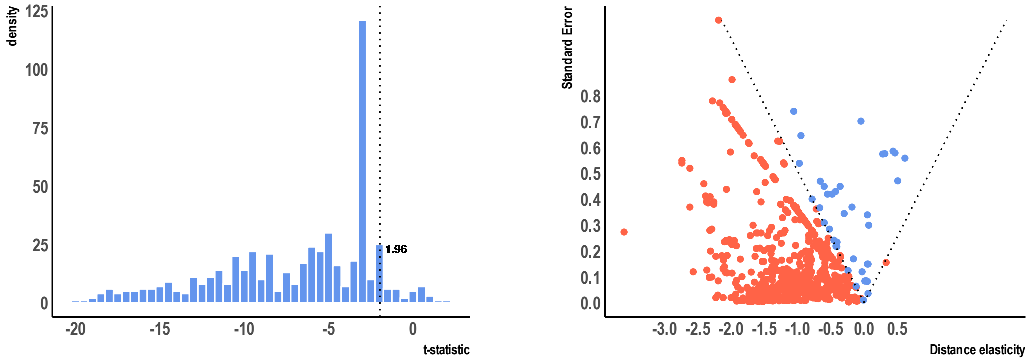

Figure 5: Histogram of t-statistics (left panel) and funnel plot of effect size versus standard error (right plot). For interpretation, t-statistics are cut off at -20 in the left panel.

Table 5 estimates various models to assess the presence and impact of publication bias. For reference the first column is our preferred specification from Table 4, being Model D. The second and third columns (AK-1 and AK-2) implement the method from Andrews and Kasy (2019) where selection is imposed with a cut-off point at a t-value of 1.96.[13] The first model assumes a normal distribution and the second model a Students-t distribution. Clearly, the implied mean effect size is now lower with a distance-decay elasticity of -0.96 for both models, pointing to the possible presence of publication bias. To investigate this further we add the standard errors s from the primary studies in a linear way to our specification in column Model D-a (see as well Stanley and Doucouliagos, 2012). Thus, true effects size are assumed to be distributed as $\gamma^{\text{true}} \sim t(\xi + \mathbf{X}\beta + \beta_s s, \sigma, \nu)$ *cf.* Model D. Column Model D-b assumes a nonlinear impact of the standard errors and implements a generalized additive model (GAM) in the form of $\sum_j \beta_j f_j(s)$, where β_j is normally distributed with mean zero and standard deviation σ_j (see as well Wood, 2017). Finally, we check in column Model D-c for possible endogeneity of s by implementing an

[13]Estimations are done using the application at `https://maxkasy.github.io/home/metastudy/`.

instrumental variable using a control function where we instrument s with the inverse square root of primary studies' number of observation $1/\sqrt{N}$ (see as well Gechert et al., 2022).

Models D-a, Model D-b and Model D-c point towards a limited presence of publication bias, where it does not seem to impact the implied mean effect size much. One possible explanation for this limited impact is that the impact of distance is not the main focus in most primary studies. And as distance is often very precisely estimated, the effect of distance does not seem to play a large role in the selection of papers for publication. However, as Model D-a is (marginally) preferred using the loo-ic criterion, we use that specification for our meta-regression models.

Table 5: Meta-analysis regression results—publication bias models (standard errors between parentheses)

	Model D	AK-1	AK-2	Model D-a	Model D-b	Model D-c
Constant	-1.08 (0.05)***	-0.96 (0.03)***	-0.96 (0.03)***	-1.06 (0.05)***	-1.08 (0.06)***	-1.08 (0.06)***
Publication bias						
β_s				-0.23 (0.16)	0.60 (1.80)	-0.09 (0.29)
σ_j					0.29 (3.34)	
Model parameters						
σ	0.05 (0.01)***			0.05 (0.01)***	0.05 (0.01)***	0.05 (0.01)***
σ_ξ	0.52 (0.03)***			0.53 (0.03)***	0.52 (0.03)***	0.52 (0.03)***
ν	1.41 (0.14)***			1.43 (0.14)***	1.42 (0.14)***	1.43 (0.14)***
Model variant						
Response	Student's t	Normal	Student's t	Student's t	Student's t	Student's t
Varying effects	yes	no	no	yes	yes	yes
$f(s)$	no	no	no	linear	GAM	linear
IV	no	no	no	no	no	yes
Impl. mean e.s.	-1.08 (0.22)***			-1.08 (0.13)***	-1.08 (0.12)***	-1.08 (0.11)***
loo-ic	78.00	–	–	77.70	79.90	78.00
Model weights	0.31	–	–	0.34	0.12	0.23
R^2	0.69	–	–	0.70	0.70	0.70

Notes: *p<0.1; **p<0.05; ***p<0.01. All models use 870 observations, as per Subsection 2.4

3.3. Meta-regression models

In Subsection 2.2 we pose three sources for variation in the distance-decay effect: namely, differences in methods or methodology, in spatial or temporal context and in the use of mediator variables. Accordingly, Table 6 presents the outcomes of four different specifications. Column (I) only contains methods and methodological variables where our preferred specification is a gravity model where arrivals are estimated with Poisson pseudo-maximum likelihood using panel data and fixed effects, where there is both variation in origin and destination and where standard errors are not imputed (see Subsection 2.1 for the scientific foundation for this choice). Column (II) adds to our preferred specification spatial co-variates, where our preferred configuration is tourist flows between all continents both for origin and destination. In column (III) we add all mediator variables as described in Table 3. Thus, as argued in Subsection 2.2 the model as described in column (II) yields the mean *total* effect of distance on tourist flows whereas the model from column (III) gives the mean *direct* effect of distance. Finally, to assess differences across time, we add a generalized additive model (GAM) in column (IV) both for the average year of data used and the publication date. The advantages of using GAMs is that it is flexible and non-parametric and is well capable of capturing non-linear time-trends.

Table 6: Meta-analysis regression models—full models (standard errors between parentheses)

	Level	(I)	(II)	(III)	(IV)
Constant		−0.96 (0.06)***	−1.00 (0.08)***	−0.79 (0.19)***	−0.78 (0.19)***
Estimation method	Least squares	−0.19 (0.02)***	−0.19 (0.04)***	−0.17 (0.04)***	−0.18 (0.04)***
	Max. likelihood	−0.12 (0.06)*	−0.13 (0.07)*	−0.10 (0.06)	−0.11 (0.06)*
	Neg. binomial	0.03 (0.18)	−0.07 (0.19)	−0.12 (0.19)	−0.15 (0.19)
	Other	−0.21 (0.06)***	−0.20 (0.06)***	−0.24 (0.06)***	−0.24 (0.06)***
Zero inflated	Yes	0.15 (0.08)*	0.15 (0.07)**	0.13 (0.08)*	0.14 (0.07)*
Individual effect	No	0.08 (0.04)**	0.07 (0.03)**	0.07 (0.03)**	0.06 (0.03)*
	Random effects	0.03 (0.04)	0.02 (0.03)	0.02 (0.03)	0.02 (0.03)
Panel	No	−0.02 (0.08)	−0.05 (0.08)	−0.04 (0.08)	−0.01 (0.08)
Duration	Yes	0.05 (0.04)	0.04 (0.04)	0.05 (0.04)	0.05 (0.04)
Constrained	Origin	−0.12 (0.15)	−0.16 (0.17)	−0.14 (0.17)	−0.14 (0.17)
	Destination	0.06 (0.06)	0.05 (0.08)	0.06 (0.08)	0.06 (0.08)
Imputed s.e.	Yes	0.18 (0.11)	0.03 (0.12)	0.05 (0.12)	0.05 (0.12)
	Continental		−0.24 (0.12)**	−0.17 (0.12)	−0.16 (0.12)
	Country		−0.01 (0.14)	0.08 (0.14)	0.09 (0.14)
	No Europe		−0.14 (0.10)	−0.16 (0.10)*	−0.17 (0.10)*

Geography
origin

Continued on next page

Table 6 – continued from previous page

		(I)	(II)	(III)	(IV)
	No Australia		-0.12 (0.17)	-0.13 (0.16)	-0.12 (0.17)
	No Africa		0.07 (0.05)	0.05 (0.05)	0.05 (0.05)
	No North-America		0.38 (0.19)***	0.38 (0.18)***	0.38 (0.19)***
	No South-America		-0.12 (0.07)*	-0.13 (0.08)*	-0.13 (0.08)*
	No Asia		-0.07 (0.12)	-0.03 (0.13)	-0.03 (0.14)
	Continental		0.00 (0.07)	-0.02 (0.07)	-0.01 (0.07)
	Country		0.16 (0.11)	0.32 (0.12)**	0.32 (0.13)**
	No Europe		-0.19 (0.04)***	-0.20 (0.04)***	-0.20 (0.04)***
Geography destination	No Australia		-0.21 (0.05)***	-0.19 (0.05)***	-0.19 (0.05)***
	No Africa		0.06 (0.03)*	0.07 (0.03)*	0.07 (0.03)**
	No North-America		-0.01 (0.09)	-0.00 (0.09)	-0.00 (0.09)
	No South-America		0.11 (0.09)	0.11 (0.08)	0.11 (0.08)
	No Asia		0.35 (0.06)***	0.34 (0.05)***	0.34 (0.05)***
	Controls for				
$\text{GDP}_{\text{origin}}$	No			-0.04 (0.12)	-0.04 (0.12)
GDP per $\text{capita}_{\text{origin}}$	No			-0.01 (0.11)	-0.01 (0.11)
$\text{Population}_{\text{origin}}$	No			0.11 (0.09)	0.11 (0.10)
$\text{GDP}_{\text{destination}}$	No			-0.04 (0.12)	-0.04 (0.13)
GDP per $\text{capita}_{\text{destination}}$	No			0.05 (0.10)	0.04 (0.11)
$\text{Population}_{\text{destination}}$	No			-0.12 (0.08)	-0.11 (0.08)
Colony	No			0.05 (0.11)	0.04 (0.11)
Language	No			-0.10 (0.06)*	-0.09 (0.06)*
Common border	No			-0.15 (0.10)	-0.14 (0.10)
Exchange rate	No			-0.11 (0.06)**	-0.11 (0.06)**
Common currency	No			-0.01 (0.09)	0.01 (0.09)
Regional trade agreement	No			-0.21 (0.08)**	-0.23 (0.08)**
Price ratio	No			-0.14 (0.06)**	-0.15 (0.06)**
World heritage site	No			0.09 (0.05)*	0.09 (0.05)*
Island	No			0.15 (0.06)**	0.16 (0.06)***
Climate	No			0.06 (0.06)	0.06 (0.06)
Sea	No			-0.09 (0.05)	-0.09 (0.05)
Politics	No			0.05 (0.04)	0.05 (0.04)
Culture	No			0.04 (0.03)	0.04 (0.03)
Religion	No			0.02 (0.06)	0.01 (0.06)
Trade	No			-0.01 (0.04)	-0.00 (0.03)
Migration	No			-0.03 (0.05)	-0.03 (0.05)
Disease	No			-0.08 (0.10)	-0.09 (0.10)
Publication bias					
β_{s_i}		-0.37 (0.15)**	-0.20 (0.16)	-0.22 (0.16)	-0.26 (0.16)
Model parameters					
σ		0.05 (0.01)***	0.04 (0.01)***	0.05 (0.01)***	0.04 (0.01)***
σ_s		0.50 (0.03)***	0.48 (0.04)***	0.46 (0.04)***	0.46 (0.04)***
ν		1.44 (0.13)***	1.57 (0.16)***	1.69 (0.19)***	1.61 (0.18)***
Study varying effects		Yes	Yes	Yes	Yes
Errors-in-outcomes		Yes	Yes	Yes	Yes
Response variable		Student's t	Student's t	Student's t	Student's t

Continued on next page

Table 6 – continued from previous page

	(I)	(II)	(III)	(IV)
Time trends	No	No	No	Yes
Implied mean effect size	-0.99 (0.08)***	-1.05 (0.04)***	-0.84 (0.03)***	-0.83 (0.04)***
Loo-ic	-24.30	-110.60	-83.90	-99.90
Model weights	0.00	1.00	0.00	0.00
R^2	0.70	0.73	0.73	0.73

Notes 1: *p<0.1; **p<0.05; ***p<0.01. All models use 870 observations, as per Subsection 2.4

Specification (I) shows that the mean effect size for our preferred specification now becomes very close to minus one. Or, the distance-decay effect changes from elastic to (almost) unit elasticity. Moreover, estimation method matters greatly for the size of the distance-decay effect. Almost all other methods than PPML yield more elastic distance-decay effects. Interestingly, the use of panel or fixed or random effects does not seem to have a large impact on effect size, neither does constrained origin or destinations. Finally, studies that do not report standard errors or t-statistics do not seem to have statistically different effect sizes.

Specification (II) adds spatial variables, where our preferred specification is tourism flows between all continents. The mean effect size now drops to -1.05, but is statistically not significantly different from minus unit elasticity. However, whether we measure tourism flows over continents, within continents or even within countries does not seem to matter much. What does seem to matter is removing North-America as an origin, which flattens the distance-decay curve considerably with 0.38. Removing Australia and Europe as destinations though steepens the distance-decay function. Finally, Asian destination countries also seem to face steeper distance-decay functions as removing the destination Asia from our specification flattens the distance-decay function with 0.35.

Specification (III) adds all mediator variables as discussed in Table 3. Most of them do not seem to affect the total impact of distance on tourism flows much. Mostly the economic mediator variables, notably exchange rate, regional trade agreement and price ratio together with common border flattens the (direct) distance-decay effect, whereas especially being an island and to a lesser extent the presence of World Heritage sites steepens the distance-decay curve. All these effects are conform prior expectations as

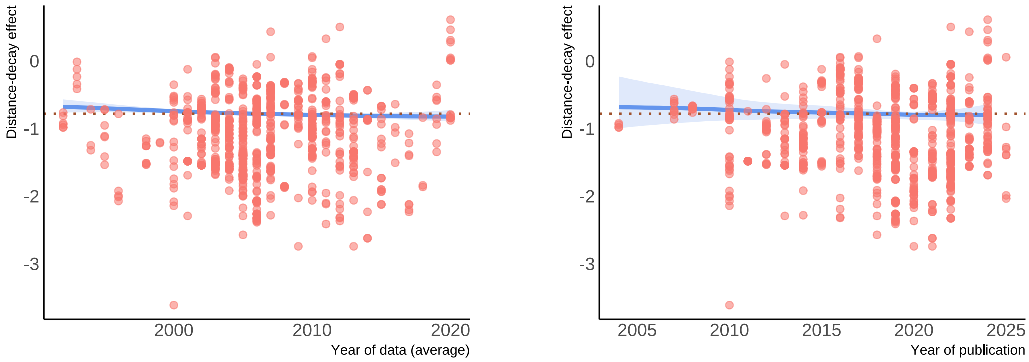

Figure 6: Time trends in blue for average year of data (left panel) and year of publication (right panel). Dotted lines indicates mean effect size (intercept). Points denote observed effect sizes.

explained in 2.2, although perhaps less so for exchange rate and price ratio. Speculating, it could be that these variables only affect tourism flows significantly when distances are small, generating perhaps (cross-border) tourism flows also induced by economic motives. Interestingly, the direct effect of distance drops further to -0.84 and is now statistically significantly different from -1. Thus, when taking all mediator effects together, the distance-decay effect becomes flatter caused by the fact that most mediator variables work at short distance (see Figure 2). The fact that the loo-ic of specification (III) is worse than that of specification (II) stipulates again that the mediator variables do not help in explaining the distance-decay effect. What they do instead is decomposing the total effect of distance in a direct and indirect effect.

Finally, specification (IV) is similar to specification (III) but with time trends added for average year of data and year of publication. Figure 6 gives the results of these time trends modeled as generative additive models (GAMs). Clearly, although there is quite some variation among observed effect sizes, the mean effect size does not change over time, neither for average year of data nor for year of publication. Interestingly, the loo-ic of specification (IV) is worse than that of specification (II) indicating that adding a time trend indeed does not improve model performance.

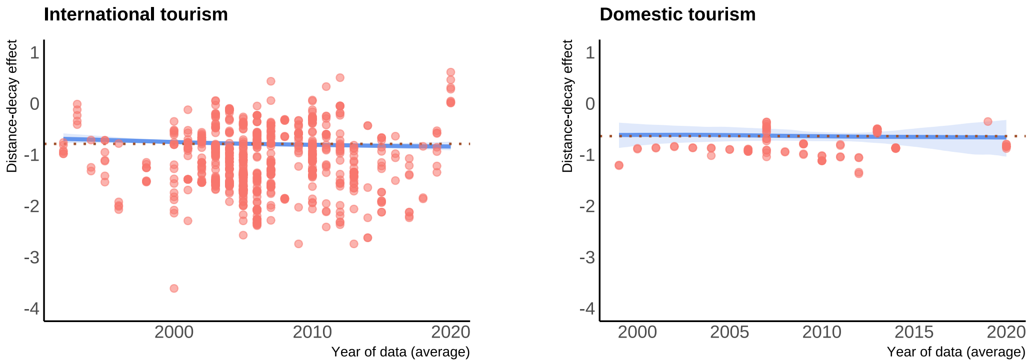

Figure 7: Time trends (average year of data) in blue for international tourism (left panel) and domestic tourism (right panel) separately. Dotted lines indicates implied mean effect sizes—for international tourism that is -0.85 with standard error 0.03, for domestic tourism that is -0.74 with standard error 0.09. Points denote observed effect sizes.

4. Discussion

The previous section shows that the distance-decay effect is moderated by methodological, methods and contextual variables and mediated by a small selection of variables dealing with the type of dyadic relation between origin and destination or the attractiveness of the destination itself. The latter sort of variables do not seem to impact the total effect of distance. On the contrary, we find evidence that the relation is in the opposite direction where there is a structural relation between distance and specific destinations or origin-destination combinations. Namely, countries sharing a common border or a regional trade agreement are usually close to each other, whereas island destinations are usually to be found at greater distances. Nevertheless, our results do say something indirectly about the impact of these variables on tourism flows. As an island destination part of the inevitable negative effect of larger distances is likely to be offset by the attractiveness of the destination itself. Thus, remote destinations with large amounts of cultural and environmental amenities can defy to a certain extent the negative effect of distance on tourism.

One intriguing finding (similar to the findings of Disdier and Head, 2008; Linders et al., 2011, for trade flows) is that the distance-decay elasticity is remarkably persistent over time. A possible explanation for this provided by the recent trade literature (see, e.g. Bergstrand et al., 2015) is that in recent decades tourism flows have shifted from domestic to international tourism—that is, a change in the *extensive* margin of international tourism (Rosselló-Nadal and Santana-Gallego, 2024). And because of possibly less friction costs domestically, distance-decay effects are arguably more elastic in international tourism than in domestic tourism. To assess this possible explanation, Figure 7 shows time trends for two separate samples, international tourism in the left panel and domestic tourism in the right panel. We again do not find changes over time both for domestic and for international tourism. Moreover, the distance-decay effects are statistically similar for international (-0.85 with standard error 0.03) and domestic tourism (-0.74 with standard error 0.09), although the results point to a larger distance-decay effect for international tourism compared to domestic tourism. Moreover, given the stable distance-decay effects, any change from domestic to international tourism would point to a temporal level effect. On the other hand, given the small number of observations here for domestic tourism, there is certainly a need for further research. And, ideally, such a primary study should combine data on both domestic and international tourism in one analysis.

In addition, our findings are similar to those found in the international trade literature (see, e.g. Anderson and Van Wincoop, 2003), even though our mean estimated distance-decay parameter is constituted by a heterogeneity (ϵ) and income share parameter (β), whilst in the international trade literature similar distance-decay parameters are estimated but then theoretically based upon the elasticity of substitution. Interestingly, and seemingly regardless of the specific underlying theoretical framework, this points to a general effect of distance on these specific forms of spatial interaction—whether that be trade of goods or tourists. In our case, the implied mean distance-decay effect should theoretically be decomposed in a heterogeneity (ϵ), an income share (β), and a 'true' distance-decay (γ) parameter as follows $-(1-\beta)\epsilon\gamma = -0.99$. In the literature, ϵ is usually estimated between 3 and 8 (Donovan et al., 2022), whereas the mean income share for tourism most likely does not exceed 0.1 (and probably is quite a bit lower). This implies that our estimate is an underestimation of the 'true' distance-decay effect (γ) not affected by market structure or (heterogeneity) in preferences.

Thus, our results indicate that the effect of distance contextually varies over space, but not over time. It is as well impacted by the choice of methodology and methods, although from a theoretical perspective there is a preferred specification. That is, an estimator able to control for heteroskedasticity and zero observations using panel data including (at least) origin and destination specific effects. Moreover, the choice of including specific mediator variables, whether they measure push, pull or dyadic factors, does not impact

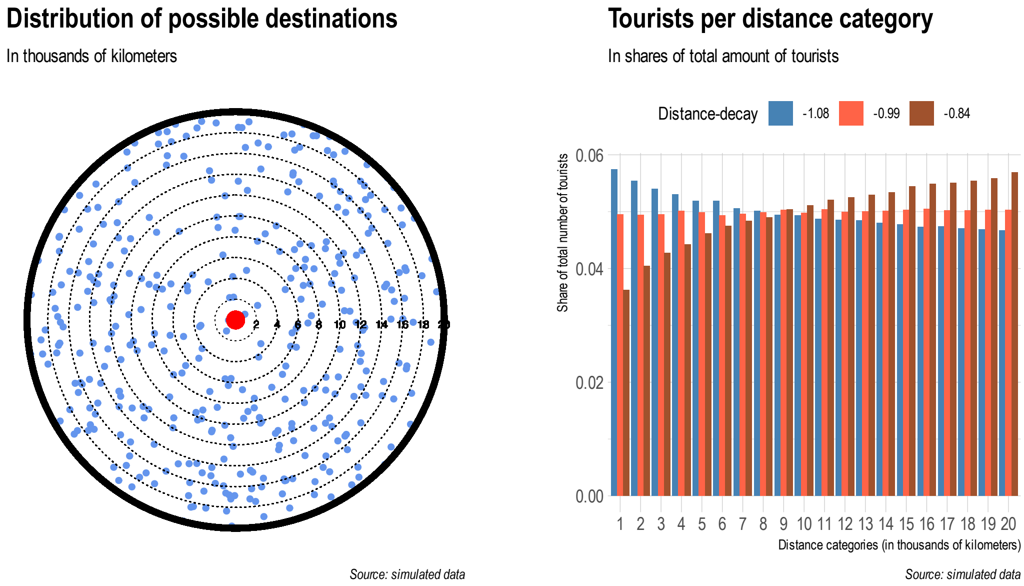

Figure 8: Simulation of estimated total amount of tourists with various distance-decay effects (-1.08, -0.99 and -0.84, respectively). The left panel gives an example of the simulated data, where distance categories are given in concentric rings, ranging from 0 to 20,000 kilometers with steps of 2,000 kilometers in between, and where the red dot denotes the origin and the blue dots possible destinations. The right panel shows the implied total amount of tourists for each distance category and each estimated distance-decay effect (*cf.* Tables 6 and 5).

the *total* effect of distance. From that perspective, the distance-decay effect seems remarkably consistent in its external validity.

The last point we would like to raise is the specification of the distance-decay function itself. Subsection 2.1 shows that exponential functions are theoretically to be preferred over power-law type of functions as the impact of distance should disappear at a distance of zero. Indeed, most recent studies in regional and urban economics use the former (*cf.* Ahlfeldt et al., 2015). Empirically, this choice is not innocuous as both types of functions predict rather different tourist flows for larger distances. Exponential-type distance-decay functions converge relatively quickly to zero for larger distances, whereas power-law-type of functions have much “fatter” tails. And, arguably, large tails model empirically tourism flows better than zero tourists for larger distances.

However, if we take these large tails into account in combination with the results from our meta-analysis, then inelastic distance-decay effects have serious consequences for

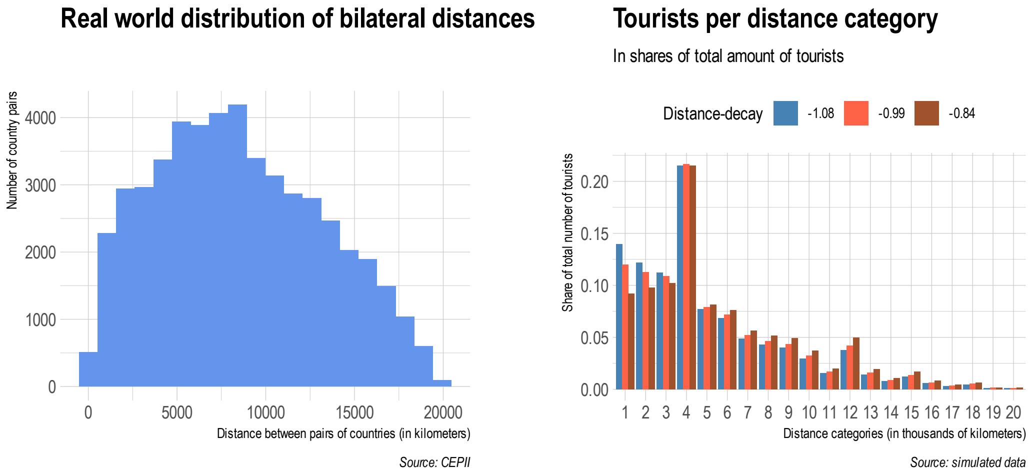

Figure 9: Real world-wide distribution of pairwise distances (left panel) and predicted shares of total tourists using $T_{od} = \frac{P_o P_d}{\tau_{od}^{\gamma}}$ where P denotes population and τ_{od} bilateral distance for various distance-decay functions γ (right panel).

the *total* amount of tourists. To illustrate, Figure 8 simulates total amount of tourists in continuous space with three types of distance-decay effects resulting from our meta-analysis: the general mean effect size (being -1.08), the total mean effect size from our preferred specification (-0.99), and the direct mean effect size when including all mediator variables (-0.84)—where the last one can be interpreted as the direct effect of *physical* distance. If we assume that destinations are homogeneously distributed over space then the total amount of tourists does not decrease but remains constant (for our preferred specification) or even increases (when looking at the direct physical effect of distance) when moving further away from the origin.[14] This may have severe environmental consequences, especially because the number of tourists are projected to grow in the near future as more and more (potential) tourists start earning enough to travel (abroad)—even though post-COVID recovery is still feeble in some tourism destinations (OECD, 2020; OECD, 2022).

Obviously, the world is not a perfectly homogeneous two-dimensional plane, whereas distances are instead governed by geography and national borders. Figure 9 shows in the left panel the real distribution of distances between all countries in the world.[15] It is

[14]Another way of seeing this is that total marginal amount of tourists—that is the circumference times the distance-decay effect—equals $2\pi d d^{\gamma} = 2\pi d^{1+\gamma}$. So, if $\gamma > -1$ total amount of tourists would—theoretically—only increase over distance.

[15]Bilateral distances are obtained from CEPII database (see Mayer and Zignago, 2011).

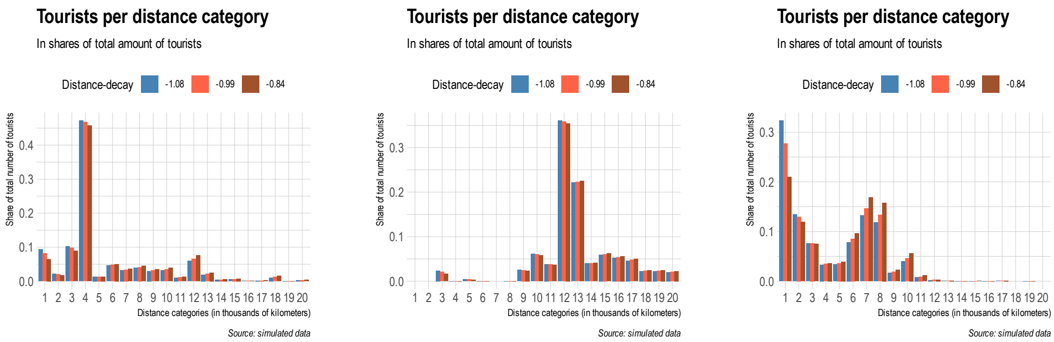

Figure 10: Shares of tourists per distance category for China, New-Zealand and The Netherlands, respectively
.

noteworthy that the majority of distance pairs are around 8,000–9,000 kilometres beyond which it tapers off quickly (which has mostly to do with the location of the Pacific ocean). If we now simulate the real share of tourists per distance category using only population in origin and destination then shares are constant for the first 3,000 kilometers and then has a very large spike around 4,000 kilometers coinciding with the distance between China and India (right panel of Figure 9). After 4,000 kilometers they slowly decrease, indicating the nearby-ness of densely populated areas.

Clearly, Figure 9 provides a very general picture and may indeed be very different for individual countries. Figure 10 provides similar simulations as in the right panel of Figure 9, but then for China, New-Zealand and the Netherlands, respectively. These countries are chosen for either their population size, absolute geographical location or relative geographical location, where the latter indicates that the Netherland are located close to numerous other relatively small and densely populated countries. Notable, for every type of country, and when we only look at the direct effect of distance, the amount of total tourists do not necessarily decrease with distance (if at all) when controlling for location and population size.

5. Conclusion

Despite the increasing availability of connections within and between countries and the lowering costs of transportation, tourist flows are still strongly influenced by distance.

The meta-analysis performed in this paper confirms this by analyzing 870 estimates from 139 primary studies applying gravity models to tourist flows. Even though we find large heterogeneity across the studies sampled which mostly correlates with (unobserved) study characteristics, estimation methods, and locations of origin and destination, the discouraging effect of distance on tourism flows is a common and consistent trait characterizing almost all of them as we find an average distance decay effect for our preferred specification close to minus unit elasticity of -0.99. Moreover, we show that this is a total effect as distance is associated with other mediator variables as well. The direct effect of distance is even smaller in absolute value with a value of -0.84. In addition, we document a wide range of mediator variables which are themselves related with distance, such as adjacency, world heritage sites, exchange rates and island destinations.

Comparable with previous research, both in tourism and trade, we do not find changes in the distance-decay effect over the last 25 years. This finding holds both for international as well as domestic tourism, where we also find similar implied mean distance-decay effects for both types of tourism, implying that the extensive margin of international tourism flows is not very important—at least for the last two and a half decades. Finally, we argue that inelastic distance-decay effects imply (theoretically at least) that the total amount of tourists increases in distance.

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Appendix A Appendix: Summary Statistics per Study

Table A: Studies and studies' summary statistics of the distance decay effect for the benchmark sample

Study	Number of Estimates	Mean	Minimum	Maximum
Akter et al. (2017)	1	−0.91	−0.91	−0.91
Alderighi and Gaggero (2019)	8	−0.38	−0.50	−0.26
Altaf (2021)	3	−0.59	−0.59	−0.59
Alvarez-Diaz et al. (2020)	2	−1.35	−1.37	−1.34
Artal-Tur et al. (n.d.)	3	−0.98	−1.44	−0.70
Balli et al. (2013)	4	−0.90	−0.94	−0.87
Balli et al. (2018)	4	−1.02	−1.08	−0.97
Balli et al. (2016)	10	−0.58	−1.48	−0.19
Bao and Xie (2019)	4	−0.95	−1.21	−0.68
Belgodere et al. (2022)	1	−1.72	−1.72	−1.72
Bi and Lehto (2018)	2	−2.43	−2.57	−2.29
Cafiso et al. (2018)	30	−0.93	−1.06	−0.83
Carril-Caccia et al. (2024)	4	−1.04	−1.50	−0.64
Cevik (2022)	19	−1.28	−1.93	−0.23
Cheung and Saha (2015)	8	−0.32	−0.38	−0.29
Chi et al. (2024)	3	−1.63	−1.69	−1.52
Chibet et al. (2014)	2	−0.56	−0.66	−0.45
Chow and Tsui (2019)	12	−0.57	−1.04	−0.36
Culiuc (2014)	20	−1.22	−1.92	−0.77
Czaika and Neumayer (2020)	3	−0.66	−0.85	−0.56
Deluna Jr and Jeon (2014)	1	−0.38	−0.38	−0.38
Deng and Hu (2019)	2	−2.26	−2.41	−2.10
Drapkin et al. (2024)	4	−0.78	−0.78	−0.77
Dropsy et al. (2020)	20	−1.94	−2.17	−1.73
Eilat and Einav (2004)	4	−0.96	−0.98	−0.92
Eryiğit et al. (2010)	4	−2.19	−3.61	−1.47
Fourie et al. (2015)	6	−1.51	−1.56	−1.48
Fourie et al. (2016)	2	−1.51	−1.51	−1.51
Fourie and Santana-Gallego (2011)	6	−1.48	−1.48	−1.48
Fourie and Santana-Gallego (2013a)	11	−1.40	−1.54	−1.15
Fourie and Santana-Gallego (2013b)	5	−1.31	−1.49	−1.06
Fourie and Santana-Gallego (2022)	4	−1.66	−1.76	−1.63
Galli et al. (2016)	1	−2.19	−2.19	−2.19
Gani and Al-Kharusi (2024)	5	−0.53	−0.60	−0.24
Gani and Clemes (2017)	12	−0.29	−0.37	−0.12
Gani and Clemes (2021)	6	−0.49	−0.58	−0.33
Gavriilidis (2021)	2	−0.93	−1.15	−0.72
Genç (2013)	2	−1.28	−1.32	−1.25
Ghalia et al. (2019)	11	−1.04	−1.42	−0.55
Ghani (2016)	2	−2.32	−2.32	−2.31
Ghani (2019)	16	−1.56	−1.62	−1.51
Ghosh et al. (2017)	8	−0.72	−0.97	−0.41
Gil-Pareja et al. (2007)	9	−0.69	−0.86	−0.56
Gormus and Göçer (2010)	11	−0.83	−0.87	−0.79

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Table A—continued from previous page

Study	Number of Estimates	Mean	Minimum	Maximum
Goswami et al. (2024)	8	0.22	0.01	0.61
Gouveia et al. (2017)	2	−1.20	−1.21	−1.19
Groizard and Santana-Gallego (2018)	2	−1.41	−1.42	−1.41
Guedes et al. (2022)	10	−0.51	−1.62	0.51
Harb and Bassil (2020a)	1	−0.86	−0.86	−0.86
Harb and Bassil (2020b)	3	−0.40	−0.40	−0.40
Hartarto and Azizurrohman (2022)	6	−1.59	−2.06	−1.26
Hartarto et al. (2022)	2	−1.85	−1.86	−1.84
Heriqbaldi et al. (2023)	6	−1.42	−1.56	−1.14
Huang et al. (2012)	6	−1.48	−1.53	−1.38
Ibragimov et al. (2021)	4	−1.73	−2.74	−1.02
Karaman (2016)	4	−0.72	−1.11	−0.44
Karmimov et al. (2023)	4	−0.80	−0.86	−0.62
Keum (2010)	4	−2.00	−2.07	−1.92
Khalid et al. (2020a)	3	−1.75	−1.75	−1.75
Khalid et al. (2021)	20	−1.49	−1.71	−1.10
Khalid et al. (2022)	18	−1.50	−1.85	−1.10
Khalid et al. (2020b)	2	−1.56	−1.68	−1.45
Kuka et al. (2021)	3	−0.67	−0.67	−0.66
Leitão (2010)	2	−0.70	−0.83	−0.57
Lien et al. (2014)	6	−1.16	−2.28	−0.54
Lien et al. (2017)	25	−0.87	−1.62	0.07
Lin et al. (2022)	7	−0.83	−0.88	−0.79
Liou et al. (2020)	1	−2.74	−2.74	−2.74
Llano et al. (2023)	11	−0.89	−1.39	0.44
Llorca-Vivero† (2008)	6	−0.69	−0.71	−0.66
Lo et al. (2023)	48	−1.06	−2.33	−0.35
Malaj and Kapiki (2016)	1	−0.83	−0.83	−0.83
Malaj and Malaj (2023)	1	−1.38	−1.38	−1.38
Marrocu and Paci (2013)	4	−0.79	−0.79	−0.78
Marti and Puertas (2017)	3	−0.32	−0.42	−0.25
Matsuura and Saito (2022)	1	−0.35	−0.35	−0.35
McKay and Tekleselassie (2018)	12	−1.18	−1.39	−0.99
Muhammad and Andrews (2008)	2	−0.71	−0.76	−0.66
Muñoz et al. (2021)	14	−0.53	−0.58	−0.49
Neumayer (2010)	6	−0.44	−0.58	−0.31
Oh and Zhong (2016)	3	−1.18	−2.02	−0.30
Okafor et al. (2021a)	1	−1.66	−1.66	−1.66
Okafor and Khalid (2021)	1	−1.75	−1.75	−1.75
Okafor et al. (2021b)	4	−1.57	−1.72	−1.44
Okafor et al. (2023)	8	−1.30	−1.30	−1.29
Okafor et al. (2018)	20	−1.62	−2.00	−1.11
Okafor et al. (2021c)	4	−0.46	−0.55	−0.36
Paniagua et al. (2022)	8	−0.82	−0.94	−0.59
Panzera et al. (2021)	4	−2.17	−2.23	−2.12
Park and Jang (2014)	3	−1.25	−1.29	−1.23
Patuelli et al. (2013)	1	−1.02	−1.02	−1.02
Pham et al. (2023)	4	−0.93	−1.12	−0.81

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Table A—continued from previous page

Study	Number of Estimates	Mean	Minimum	Maximum
Pintassilgo et al. (2016)	1	−1.59	−1.59	−1.59
Pompili et al. (2019)	2	−1.04	−1.11	−0.97
Priego et al. (2015)	2	−0.89	−0.90	−0.89
Provenzano (2020)	3	−0.64	−0.65	−0.64
Provenzano and Baggio (2017)	4	−0.65	−0.86	−0.57
Puah et al. (2019)	2	−0.43	−0.43	−0.43
Qin et al. (2023)	2	−1.55	−1.55	−1.55
Rey et al. (2011)	1	−0.74	−0.74	−0.74
Rosselló-Nadal and Santana-Gallego (2014)	2	−1.58	−1.58	−1.58
Rosselló-Nadal and Santana-Gallego (2024a)	3	−0.56	−0.58	−0.53
Rosselló-Nadal and Santana-Gallego (2024b)	28	−1.03	−1.34	−0.53
Rosselló-Nadal et al. (2017)	5	−1.30	−1.32	−1.28
Saayman et al. (2016)	16	−0.55	−1.20	0.06
Salahodjaev et al. (2020)	4	−2.01	−2.37	−1.57
Santana-Gallego et al. (2010a)	6	−0.64	−0.80	−0.53
Santana-Gallego et al. (2010b)	3	−0.86	−1.02	−0.70
Santeramo (2015)	8	−0.73	−0.92	−0.12
Santeramo and Morelli (2016)	10	−0.12	−0.18	−0.09
Santeramo et al. (2017)	4	−1.12	−1.12	−1.11
Seetanah et al. (2010)	5	−0.22	−0.41	−0.01
Shafiullah et al. (2022)	6	−1.86	−1.87	−1.85
Shah et al. (2022)	2	−0.61	−0.78	−0.43
Siskos and Darvidou (2018)	6	−1.02	−2.12	0.33
Song (2010)	2	−1.47	−1.53	−1.41
Tang (2021)	4	−2.28	−2.62	−1.64
Tang and Zhang (2025)	8	−1.28	−2.03	0.06
Tangvitoontham and Sattayanuwat (2022)	3	−1.23	−1.40	−1.07
Tveteras and Roll (2014)	1	−1.10	−1.10	−1.10
Velasquez and Oh (2013)	4	−0.95	−2.29	−0.05
Vierhaus (2019)	5	−1.22	−1.25	−1.15
Vietze (2012)	12	−0.91	−1.05	−0.26
Viljoen et al. (2019)	20	−2.19	−2.38	−2.06
Voltes-Dorta et al. (2016)	2	−0.81	−0.82	−0.80
Xu and Dong (2020)	8	−1.34	−1.36	−1.34
Xu et al. (2019)	16	−1.21	−1.40	−0.94
Yang et al. (2019a)	12	−0.87	−0.88	−0.86
Yang and Lin (2014)	7	−1.46	−1.53	−1.15
Yang et al. (2010)	5	−1.57	−1.67	−1.42
Yang et al. (2019b)	8	−0.89	−0.95	−0.88
Yang and Wong (2012)	1	−0.71	−0.71	−0.71
Yerdelen and Gul (2019)	2	−0.21	−0.23	−0.19
Zhang and Findlay (2014)	2	−1.29	−1.35	−1.24
Zhang et al. (2019)	2	−1.52	−1.54	−1.51
Zhu and Liu (2022)	1	−1.74	−1.74	−1.74
De Vita (2014)	3	−0.78	−0.81	−0.76
Özdemir and Tosun (2022)	1	−0.88	−0.88	−0.88
Total	870	−1.09	−3.61	0.61

Appendix B Studies sampled

Sampled studies in the meta-analysis

Akter, H., S. Akhtar and S. Ali (2017). 'Tourism demand in Bangladesh: Gravity model analysis'. *Tourism: An International Interdisciplinary Journal* 65.3, pp. 346–360.

Alderighi, M. and A. A. Gaggero (2019). 'Flight availability and international tourism flows'. *Annals of Tourism Research* 79, p. 102642.

Altaf, N. (2021). 'Modelling the international tourist arrivals in India'. *Tourism Planning & Development* 18.6, pp. 699–708.

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Balli, F., H. O. Balli and R. J. Louis (2016). 'The impacts of immigrants and institutions on bilateral tourism flows'. *Tourism Management* 52, pp. 221–229.

Balli, F., H. O. Balli and K. Cebeci (2013). 'Impacts of Exported Turkish Soap Operas and Visa-Free Entry on Inbound Tourism to Turkey'. *Tourism Management* 37, pp. 186–192.

Bao, J. and H. J. Xie (2019). 'Determinants of domestic tourism demand for Guilin'. *Journal of China Tourism Research* 15.1, pp. 1–14.

Belgodere, A., S. Giannoni and S. Noblet (2022). 'Are good institutions required to import economic growth? The case of tourism'. *Tourism Economics* 28.7, pp. 1943–1955.

Bi, J. and X. Y. Lehto (2018). 'Impact of cultural distance on international destination choices: The case of Chinese outbound travelers'. *International Journal of Tourism Research* 20.1, pp. 50–59.

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Chibet, R. et al. (2014). 'Tourist Flows and Factors Attractiveness in Southern Mediterranean Countries'. *Journal Transition Studies Review* 21.1, pp. 161–171.

Chow, C. K. W. and W. H. K. Tsui (2019). 'Cross-border tourism: Case study of inbound Russian visitor arrivals to China'. *International journal of tourism research* 21.5, pp. 693–711.

Culiuc, A. (2014). 'Determinants of International Tourism-Imf Working Paper No. 14/82'. *Retrieved from Washington*.

Czaika, M. and E. Neumayer (2020). ‘On the negative impact of time zone differences on international tourism’. *Current Issues in Tourism* 23.10, pp. 1181–1185.

De Vita, G. (2014). ‘The Long-Run Impact of Exchange Rate Regimes on International Tourism Flows’. *Tourism Management* 45, pp. 226–233.

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Eilat, Y. and L. Einav (2004). ‘Determinants of International Tourism: A Three-Dimensional Panel Data Analysis’. *Applied Economics* 36.12, pp. 1315–1327.

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Gani, A. and S. Al-Kharusi (2024). ‘Exploring Oman’s International Tourism Determinants in a Gravity Modelling Framework’. *Perspectives on Global Development and Technology* 22.5-6, pp. 303–320.

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