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Social Connectedness and Tourism Demand

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The importance of tourism and its contribution to the global economy is unanimously acknowledged. In 2019 alone, travel and tourism accounted for 10.3% of global GDP (WTTC, 2020). To that extent, it is of great importance to tourism professionals and policy makers in destination countries to identify the demand factors of their product. Perhaps, it is due to this necessity that the academic literature on tourism demand has been growing significantly over the past years. Apart from the traditional, and widely examined, determinants of tourism demand (income, etc.), studies now utilize a wide range of variables, such as mood and sentiment (Dragouni, Filis, Gavriilidis, and Santamaria, 2016), cultural affinity (Fourie and Santana-Gallego, 2013) and climate change (Ma and Kirilenko, 2020), among others. This study introduces another potential determinant of tourism demand; the level of social connectedness between origin and destination countries.

Social networks play a very important role in people's decision making. Yet till recently, it was very difficult to quantify the level of social connectedness between geographic regions, or countries, at a large scale. Bailey, Cao, Kuchler, Stroebel, and Wong (2018) address this problem by developing a new measure of social connectedness based on Facebook friendship links and examine how social connectedness within the United States relates to various aspects. Indeed, the authors find that there is a high correlation among social connectedness, trading activity, innovation spreading and migration. Their findings are similar when they consider international trade between states and foreign countries. At a global level, Bailey, Gupta, Hillenbrand, Kuchler, Richmond, and Stroebel (2020) report that a higher social connectedness between a pair of countries translates into larger bilateral trade; their results hold after controlling for geographic distance. Finally, Bailey, Cao, Kuchler, and Stroebel (2018) examine the effect of social connectedness on the housing market and find that the social network of an individual can influence her own housing investment decisions.

Social networks are particularly relevant to the tourism industry as well since they play an important role on the propensity of people to travel. In fact, one of the key sectors of the tourism industry is

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people travelling to visit friends and relatives (VFR), i.e. people on their social network. For instance, Casado-Díaz, Casado-Díaz, and Casado-Díaz (2014), using a sample of 365 individuals from the U.K., retired and living in Spain, find that most of their subjects maintain their social capital by either travelling back home, or being visited by their family and social network from their origin country. In general, VFR comprises 27 per cent of all international visits worldwide (UNWTO, 2019), yet relevant research suggest that this figure is underestimated (Backer, 2012). This study examines the relationship between social connectedness and tourism demand, using a sample of 39 destination countries and 167 origin countries (please see Table A1 for the countries included in our sample).

To perform the analysis, we employ Bailey et al.'s (2018) Social Connectedness Index (SCI) as a proxy for social connectedness. This index is based on the number of Facebook friend connections between pairs of countries. Since its adoption in 2004, Facebook has become the largest online social network; it had over 2.6 billion monthly active users as of 2020. With it global presence (apart from certain countries where Facebook is banned, i.e. China) it can provide a good indication about the level of social connectedness between two countries. In our analysis, the SCI is based on the number of all active Facebook users as of March 2020.[1] A potential bias in our proxy for social connectedness is the fact that the SCI is based on a single social network (Facebook). It does not consider others, such as Instagram, which may be more popular in the tourism industry. Likewise, our proxy does not capture social connections on people who do not use social networks at all. The choice of the proxy is clearly driven from data availability. Having said that, our results could be downward biased and may not document the true effect of social connectedness.

Building on the theory of social capital, we posit that tourists have a propensity to travel to countries where they maintain social networks. In order to examine this hypothesis, this study employs a gravity model. Gravity models have been originally employed to examine bilateral trade flows between country pairs as a function of their economic size and other factors, which might affect trade flows (geographical distance, common language, common border, etc.). Under the assumption that tourism is a special class of trade, and given its goodness of fit, such models have been widely used in previous studies examining tourist flows between countries (Harb and Bassil, 2020; Fourie and Santana-Gallego, 2013; Gil-Pareja, Llorca-Vivero, and Martinez-Serrano, 2007). In our case, the model employed takes the following specification:

[1] For details about the construction of the index please refer to Bailey et al. (2018).

$$LN\,(Arrivals_{i,j}) \;=\; \alpha_0+\alpha_1 Ln(SCI_{i,\,j})+\theta'(G_{i,j})+\beta_i+\gamma_j+\ \varepsilon_{i,j} \qquad (1)$$

where $LN\ (Arrivals_{i,j,t})$ is the natural logarithm of the annual number of tourist arrivals from country i to country j, and $Ln(SCI_{i,\,j})$ is the natural logarithm of SCI between countries (i,j). Following previous studies that employ gravity models in the tourism literature, we also include the vector $G_{i,j}$, which reflects factors that may affect tourist flows between two countries. These factors are: the natural logarithm of GDP of the origin country (proxy for spending capacity), the natural logarithm of GDP of the destination country (proxy for destination country's infrastructure development);[2] the natural logarithm of the geographical distance between the two countries and a dummy variable for contiguity (proxies for transport costs); the natural logarithm of price differentials between the two countries, calculated as the ratio of the CPI of destination country to the CPI of the origin country times the nominal bilateral exchange; dummy variables for common official language, common colonizer post 1945, and colonial relationship post 1945 (proxies for cultural ties). In addition, β_i are origin-country fixed effects, γ_j are destination-country fixed effects, and $\varepsilon_{i,j}$ is the disturbance term. The SCI data have been provided by Facebook; data on tourism arrivals are obtained from the United Nations World Tourism Organisation (UNWTO); data on CPI and exchange rates are obtained from the World Bank, and the remaining data are obtained from CEPII's GeoDist and Gravity datasets (*distwces, contig, comlang_off, comcol, col45, gdp_o, gdp_d*). Data on tourist arrivals and the remaining variables are from year 2015. We use this year because CEPII's gravity data is available till 2015 and it allows for a more comprehensive dataset. Likewise, Bailey et al. (2018) employ SCI data from 2016 while using trading data from 2012, in order to address a similar matter. Table 1 presents the descriptive statistics of our series.

[TABLE 1 ABOUT HERE]

Model 1 in Table 2 provides the results of our baseline regression. Our findings indicate that social connectedness exhibit a positive, and highly significant, relationship with tourist arrivals. Model 2 examines the impact of the factors included in the vector $G_{i,j}$ on tourist arrivals, without the addition of the SCI variable. We notice that the GDP of destination countries is an important determinant of tourist arrivals. The variable of distance between countries is negative and significant, while

[2] Results remain qualitatively similar when we use GDP per Capita instead of GDP.

contiguity is found to exhibit a positive, and significant, relationship with tourist arrivals. Common official language, common colonizer, and colonial relationship are all positive and significant. In the third specification of our model, we include the SCI variable in addition to the variables of Model 2. Again, social connectedness exhibits a positive and significant relationship with tourism demand; the GDP of the destination country, contiguity, common colonizer, and colonial relationship are all positive and significant, while geographical distance is found to be negative and significant. Therefore, our results confirm that social connectedness is an important determinant of tourist flows between countries, even after controlling for geographic proximity and other factors.

[TABLE 2 ABOUT HERE]

The contribution of this study can be described succinctly. First, it contributes to the tourism literature by introducing another potential determinant of tourism demand, the Social Connectedness Index. Second, consistent with the concept of social capital, it highlights the importance of social networks on the propensity of people to travel. The findings of this study bear important implications for policy makers as well. For instance, as the Social Connectedness Index becomes more broadly available, future research might examine the role of social connectivity on tourist flows at a regional level.[3] Finally, destinations could utilize social connectedness to inform their tourism policies or amend their transportation infrastructure. For example, in case of notable social connectedness between two countries or regions, providing additional direct airline routes, might be profitable and also help attract additional visitors. In addition, given the recent COVID-19 outbreak, tools such as the SCI, can be of great assistance to destination countries in their effort to plan their tourism recovery strategies and invest in origin countries, or regions, with high social connectedness levels.

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[3] The Social Connectedness Index is now available for 332 European regions to any interested researcher from Facebook Data for Good (https://dataforgood.fb.com).

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Table 1: Summary Statistics

	Mean	*Max*	*Min*	*Std. Dev*	*Skewness*	*Kurtosis*	*N*	*Source*
LN(Arrivals)	8.7260	16.0120	0.0000	3.3312	-0.5565	2.7163	1722	UNWTO
Ln(SCI)	8.8316	18.0989	4.3438	1.7724	0.2811	3.2133	1722	Facebook
LN(GDP_{o})	25.4189	28.8440	20.7072	1.7596	-0.1171	2.0596	1722	CEPII
LN(GDP_{d})	25.9874	30.5234	18.8915	2.0715	-0.3491	2.7844	1722	CEPII
Ln(Distance)	7.9852	9.8269	4.1071	1.0142	-0.2779	2.3331	1722	CEPII
Ln(Price)	-0.8834	6.7512	-9.8341	2.9401	-0.3476	3.2752	1209	World Bank

Notes: The table presents the descriptive statistics of the variables (excluding dummies) employed. The variables are: the natural logarithm of tourist arrivals; the natural logarithm of SCI; the natural logarithm of origin-country GDP; the natural logarithm of destination-country GDP; the natural logarithm of geographical distance between origin and destination country; the natural logarithm of the price differential between origin and destination country, calculated as the ratio of the CPI of destination country to the CPI of the origin country times the nominal bilateral exchange. Due to missing data on CPI and exchange rates, the number of observations of Ln(Price) is smaller.

Table 2: Gravity Regressions – The Role of Social Connectedness

	Dependent variable: Ln(Arrivals)		
	(1)	(2)	(3)
Ln(SCI)	0.896***		0.478***
	(0.0241)		(0.0331)
Ln(GDP_{orig})		3.893	0.447
		(3.004)	(2.946)
Ln(GDP_{dest})		1.629***	1.546***
		(0.105)	(0.0974)
Ln(Distance)		-1.148***	-0.719***
		(0.0724)	(0.0682)
Ln(Price)		-0.0472	-0.488
		(0.365)	(0.358)
Contiguity		0.359***	0.236**
		(0.123)	(0.0969)
Common Language		0.464***	-0.00155
		(0.134)	(0.109)
Common Colonizer		1.498***	1.026***
		(0.281)	(0.230)
Colonial Relationship		1.419***	0.655***
		(0.197)	(0.198)
Constant	2.620***	80.54	-17.51
	(0.457)	(79.77)	(78.21)
Origin Country FE	YES	YES	YES
Destination Country FE	YES	YES	YES
Observations	1,722	1,209	1,209
R^2	0.938	0.944	0.956

Notes: The dependent variable is the natural logarithm of tourist arrivals from origin to destination country. The explanatory variables are: the natural logarithm of SCI between the country pair, the natural logarithm of the origin-country GDP, the natural logarithm of the destination-country GDP, the natural logarithm of the geographical distance between the two countries, the natural logarithm of price differential (adjusted by exchange rates) between the two countries, a dummy indicating contiguity, a dummy indicating common official language, and dummies indicating a common colonizer, or a colonial relationship, post 1945, between the country-pair. Fixed effects for the origin and destination country are included in all models. Robust standard errors are reported in parentheses and clustered by origin and destination country. Significance levels: *** $p<0.01$, ** $p<0.05$.

Appendix

Table A1: Sample Countries

Afghanistan	Denmark	Kiribati	Paraguay
Angola	Dominican Republic	Korea	Qatar
Albania	Algeria	Kuwait	Romania
United Arab Emirates	Ecuador	Laos	Russia
Argentina	Egypt	Lebanon	Rwanda
Armenia	Spain	Liberia	Saudi Arabia
Antigua and Barbuda	Estonia	Saint Lucia	Sudan
Australia	Ethiopia	Sri Lanka	Senegal
Austria	Finland	Lesotho	Singapore
Azerbaijan	Fiji	Lithuania	Solomon Islands
Burundi	France	Luxembourg	Sierra Leone
Belgium	Gabon	Latvia	El Salvador
Benin	United Kingdom	Macao	Somalia
Burkina Faso	Georgia	Morocco	Suriname
Bangladesh	Ghana	Moldova	Slovakia
Bulgaria	Guinea	Madagascar	Slovenia
Bahrain	Gambia	Maldives	Sweden
Bahamas	Guinea-Bissau	Mexico	Swaziland
Bosnia and Herzegovina	Equatorial Guinea	F.Y.R.O.M	Seychelles
Belarus	Greece	Mali	Chad
Belize	Grenada	Malta	Togo
Bolivia	Guatemala	Myanmar	Thailand
Brazil	Guyana	Mongolia	Tonga
Barbados	Hong Kong	Mozambique	Trinidad and Tobago
Brunei Darussalam	Honduras	Mauritius	Tunisia
Bhutan	Croatia	Malawi	Turkey
Botswana	Haiti	Malaysia	Taiwan
Central African Republic	Hungary	Namibia	Tanzania
Canada	Indonesia	Niger	Uganda
Switzerland	India	Nigeria	Ukraine
Chile	Ireland	Nicaragua	Uruguay
Côte d'Ivoire	Iraq	Netherlands	United States
Cameroon	Iceland	Norway	Uzbekistan
Congo	Israel	Nepal	Saint Vincent and the Grenadines
Colombia	Italy	New Zealand	Viet Nam
Comoros	Jamaica	Oman	Vanuatu
Cabo Verde	Jordan	Pakistan	Samoa
Costa Rica	Japan	Panama	Yemen
Cyprus	Kazakhstan	Peru	South Africa
Czech Republic	Kenya	Philippines	Zambia
Germany	Kyrgyzstan	Poland	Zimbabwe
Djibouti	Cambodia	Portugal	