Determinants of tourism destination vulnerability during the COVID-19 pandemic

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Introduction

The EU is one of the most prominent tourism destinations worldwide, drawing hundreds of millions of international visitors yearly. Since 2009, tourism in Europe observed a steady growth of nights spent of nearly 4% per annum (compound), according to Eurostat records. According to some estimates (WTTC, 2020), the travel and tourism sector contributed to a sizeable 10% of the EU's GDP and employment (direct, indirect and induced contribution) in 2019. However, with the outbreak of the COVID-19 pandemic, tourism was one of the most negatively affected sectors by the mobility and other restrictions put in place by national authorities to contain it. Also according to Eurostat, the total nights spent in 2020 dropped by an unprecedented 54% in relation to 2019, or 70% when considering only the international nights spent, revealing the exposure of the tourism sector to demand shocks.

Tourism destinations are vulnerable to several exogenous shocks driving demand down, such as natural calamities, economic, political or health crises. For instance, with respect to the latter, it has been shown that earlier epidemics, such as SARS and MERS have had impact on tourism demand (Kuo et al., 2008; McAleer et al., 2010). The body of literature analyzing the impact of COVID-19 on tourism is now starting to emerge (Assaf et al., 2022; Duro et al., 2021; Škare et al., 2021). The study by Duro et al. (2021) was one of the first identifying factors influencing regional vulnerability in the context of COVID-19 in Spain, such as tourism dependency, market structure, the supply of rural accommodation, and health incidence of the pandemic.

The concept of resilience is also key for tourism destinations aiming to be competitive in a context of shocks such as the COVID-19 pandemic but also of wider and rapid societal transformations. The concept of resilience is borrowed from the engineering field, and defined as the measure of the speed at which a system can return to its previous equilibrium (Hall et al., 2017). Here, we adopt the definition by the European Commission[1], whereby resilience can be disentangled in two dimensions: vulnerability to crisis and structural changes, and the capacity to react.

In this study, we start with the notion that, although tourism in the EU27 was strongly affected in all EU27 countries, the impact of the COVID-19 pandemic was heterogeneous across regions, coherent with the idea that vulnerability is place-specific (Calgaro et al., 2014). The objective of this study is to assess the determinants of regional tourism vulnerability in the context of the COVID-19 pandemic in 2020 in the EU27, and provide new insight for tourism policy aiming at a more resilient tourism activity.

Data and methods

Here, we assess the vulnerability of European tourism destinations at the NUTS2 level. We define vulnerability as a continuous variable in the interval from 0 to 1, where 0 identifies non-vulnerable destinations, while 1 is a theoretical maximum vulnerability. Vulnerability has been measured

[1] https://ec.europa.eu/info/sites/default/files/dashboard_report_20211129_en.pdf

proportionally to the percentage loss of night spent in response to the demand shock induced by the COVID-19 pandemic, as follows:

$$Y_i \in [0,1] = \begin{cases} 0 & for\ NS_{i,2020} \geq NS_{i,2019} \\ 1 - \frac{NS_{i,2020}}{NS_{i,2019}} & for\ NS_{i,2020} < NS_{i,2019} \end{cases} \quad (1)$$

where Y_i is the vulnerability score for tourism destination *i* (i.e., NUTS2 region) and NS_i denotes the nights spent and is measured for each destination *i* for the years 2019 and 2020. In this analysis, nights spent were retrieved from Eurostat's experimental data source on Collaborative economy platforms[2], which records the number of nights spent by all guests booking accommodation via four different platforms: Airbnb, Booking.com, Tripadvisor, and Expedia for 2019 and 2020 at NUTS2 level. Regions that do not present a loss in nights spent in 2020 compared to 2019 (16 out of 233 in the sample) have been classified as non-vulnerable to the COVID-19 shock and received a vulnerability score of 0. The closer the value to 1, the more vulnerable the destination is.

To analyze the determinants of vulnerability, we use a two-step fractional response model (Ramalho et al., 2011). The model is composed of two components: a binary component indicating if a region is vulnerable or not (i.e. Y_i being >0 or 0), and a fractional component, capturing the intensity of vulnerability ($Y_i \in (0,1]$). The first step is a binary logit model, with a dichotomous dependent variable in which values 0 means not vulnerable, and 1 means vulnerable. This is estimated by maximum likelihood. The second step is a fractional model, analyzed through a generalized linear model fashion, estimated by Bernoulli-based quasi-maximum likelihood.

In terms of explanatory variables, we considered destination-specific tourism characteristics as determinants of destination vulnerability, plus socio-economic and epidemiologic control variables. We used population density and GDP per capita as socio-economic control variables, and the average COVID-19 cases per million as epidemiologic control variable. In addition, we propose a weighted travel restriction index, to capture the impact of the COVID-19 related restrictions, which may not always correlate with epidemiological situation across time and space. The weighted restriction index is obtained by weighting the monthly Oxford stringency index at country level (Hale et al., 2021) by the monthly proportion of touristic demand at NUTS2 level, as follows:

$$WSI_i = \sum_{t=1}^{12} SI_{it,2020} * \frac{NS_{it,2019}}{NS_{i,2019}} \quad (2)$$

where:

- WSI_i = weighted stringency index of tourism destination *i*;
- $SI_{it,2020}$ = Average Oxford stringency index in the country of tourism destination *i* in month *t*;
- $NS_{it,2019}$ = Nights spent in tourism destination *i* in month *t* of 2019;
- $NS_{i,2019}$ = Nights spent in tourism destination *i* in 2019.

[2] https://ec.europa.eu/eurostat/web/experimental-statistics/collaborative-economy-platforms

As destination-specific tourism characteristics, we considered tourism intensity, seasonality, proximity demand, the share of foreign tourism, tourism diversity, and destination type, for the closest available year before the pandemic hit.

- **tourism intensity** is calculated by dividing the number of nights spent at tourist accommodations by the resident population, and is a proxy for economic dependence on tourism (Batista e Silva et al. 2018).
- **seasonality** is measured through a coefficient of variation, which is defined as the ratio between the standard deviation and the mean of nights spent by month (Bender et al., 2005).
- **proximity demand** is a measure of potential demand for each tourism destination. The indicator is expressed in millions of inhabitants and is calculated as an inverse distance weighted of the number of inhabitants within a radius of 800 km from the border of each NUTS2 region[3], as follows:

$$Q_i = \sum_j \frac{Q_{ij}}{(d_{ij}+1)} \tag{3}$$

where:

Q_i = proximity demand for tourism destination region i.

Q_{ij} = no. of inhabitants found at a distance band j from region i (distance bands from 0 to 800 km, spaced in 50 km, so: 0-50, 50-100, ..., 750-800). This is was done using GIS overlays between buffer bands and the JRC-GEOSTAT population grid 2018 at 1 km resolution[4].

d_{ij} = distance between region *i* and band *j*, measured in hundred km. When *i* = *j*, d is set to 0. This permits that the whole population of region *i* is counted as part of the proximity demand.

- **share of foreign tourism** is the percentage of international nights in relation to total nights spent in each tourism destination.
- **tourism diversity** measures the diversity of the tourism typologies within a destination. It is based on the relative presence of tourism accommodation establishments across four geographical zones within a destination: cities, coastal areas, natural or mountainous areas, and rural areas. It assumes that the location of hotels in these different geographical zones is associated with different types of tourism offer. For a given country or region, a high concentration of tourism supply (no. of tourism accommodation establishments) in one or a few types of geographical zones yields a low tourism diversity, while a balanced distribution of tourism supply across the geographical zones results in a higher tourism diversity.
- **destination type** is a classification of EU regions based on hotel location patterns and geographical criteria, based on Batista e Silva et al. (2021).

[3] The 800 km distance is considered as the limit threshold of short-haul flights (Gössling et al., 2020) in which there are attractive alternative means of transport to flights (Yin et al., 2015).

[4] https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/population-distribution-demography/geostat

Findings

Descriptive statistics show that NUTS2 regions in 2020 lost on average 33% of the nights spent compared to the previous year, with the strongest loss reaching 79% (Table 1).

Table 1. Relative change in nights spent in 2020 vs 2019

	Average	Median	Standard Deviation	Min	Max
Nights spent 2020 vs 2019	-33%	-33%	20%	-79%	+27%

Out of 233 regions, 16 recorded an increase in nights spent compared to the previous year, this happened especially in regions with low demand in the previous year (Figure 1, left). The maximum increase corresponds to +27% (Table 1). Those regions received a vulnerability score of 0, while the vulnerability score of other regions has been calculated as expressed in equation 1. Distribution of the vulnerability score is shown in Figure 1 (right).

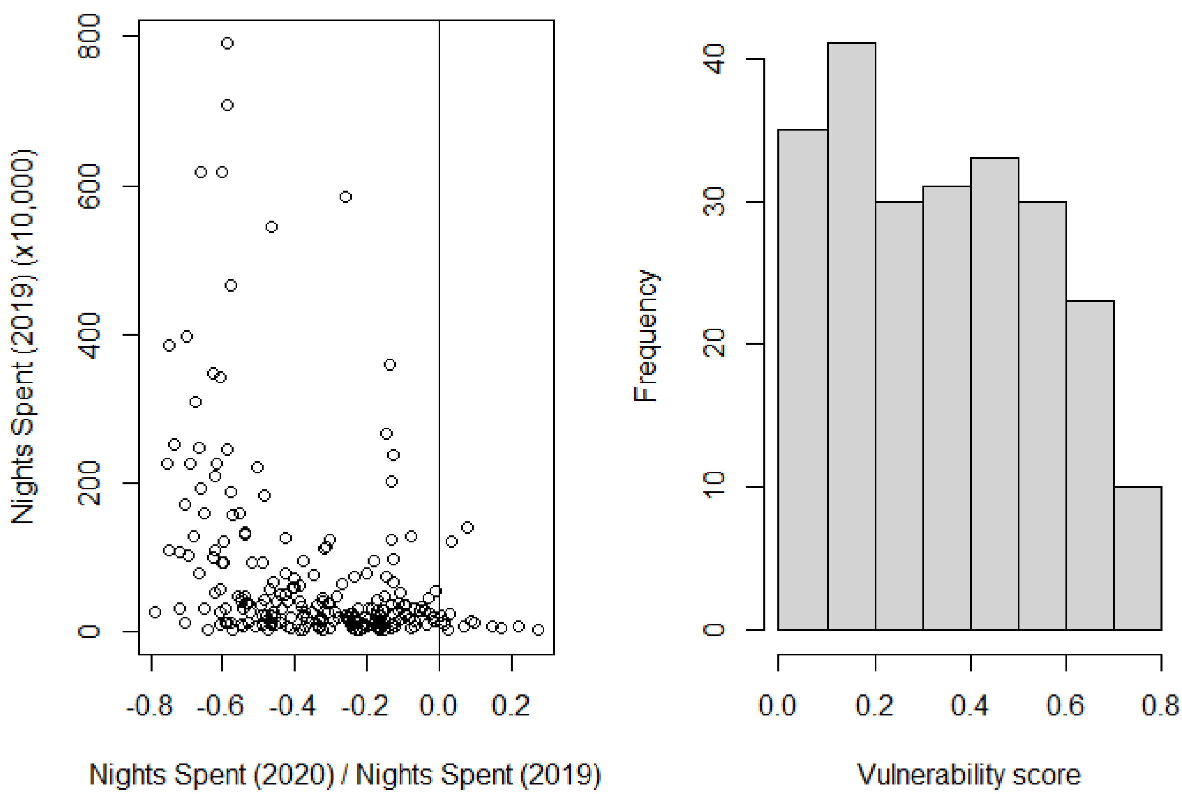
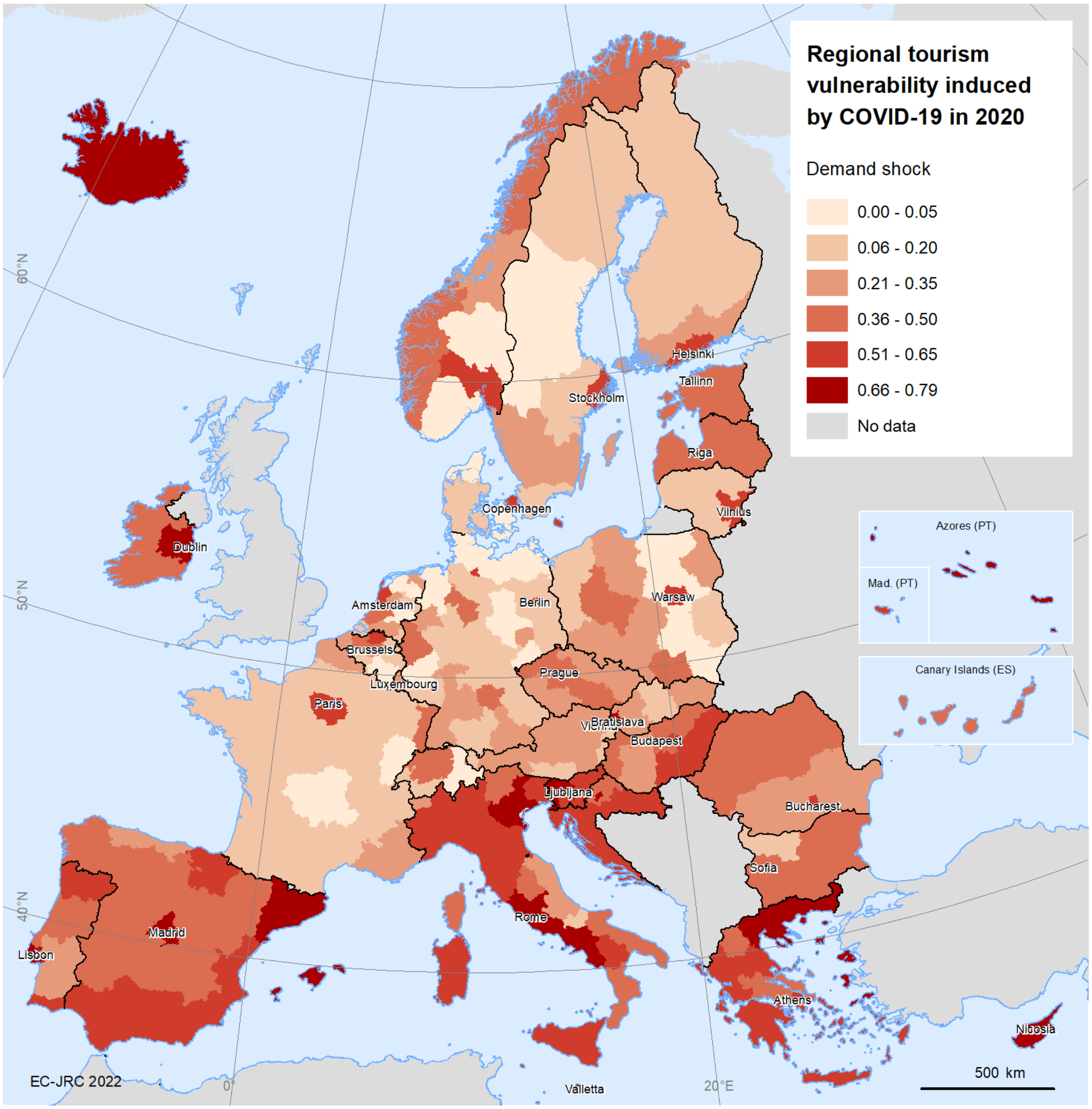


Figure 1. Percentage change of nights spent 2020 vs 2019 and vulnerability score

The distribution of the vulnerability score is asymmetric and moderately left skewed, indicating a higher frequency of vulnerability close to 0 than 1. A relevant portion of regions recorded a considerable vulnerability score between 0.2 and 0.7. The map in Figure 2 shows the geographical distribution of vulnerability of NUTS2 regions.



At a first glance, regions of the country capital cities seem to present a higher vulnerability, which is probably explained by the absence of business tourism and the closure of borders in Q2, a period in which cities have more demand to lose compared to other types of destination (e.g., coastal or mountain). Preliminary results of determinants of vulnerability are shown in Table 2. A multi-collinearity testing conducted on the independent variables reported the highest VIF of 7.5, indicating absence of collinearity issues.

Table 2. Regression results. Impact on the vulnerability score.

	Two steps model			
	Binary component		Fractional component	
	Est.	S.E.	Est.	S.E.
Proximity of demand	-0.008	(0.024)	-0.013***	(0.003)
Domestic demand	0.038	(0.024)	-0.001	(0.002)
Tourism intensity	-0.017	(0.104)	-0.006	(0.007)
Tourism seasonality	0.016	(0.018)	0.001	(0.002)
Share of foreign tourism	0.141***	(0.042)	0.025***	(0.003)
Tourism diversity	0.099***	(0.031)	0.002	(0.003)
Internet speed at destination	-0.001	(0.019)	0.002	(0.002)
Share of tourism employment	-0.058	(0.110)	-0.006	(0.010)
Type: Coastal (ref=urban mix)	-0.121	(1.325)	-0.609***	(0.163)
Type: City (ref=urban mix)			-0.048	(0.150)
Type: Rural (ref=urban mix)	-1.707*	(0.979)	-0.103	(0.161)
Type: Nature/Mountain (ref=urban mix)	0.876	(1.074)	-0.507***	(0.150)
Population density	0.945	(0.002)	0.083**	(0.004)
GDP pro capite	0.027	(0.065)	-0.001	(0.005)
Weighted Stringency Index	-0.027	(0.076)	0.042***	(0.006)
Covid cases	-0.026	(0.030)	-0.001	(0.003)
Intercept	YES		YES	
Link function	logit		logit	
Observations	233		217	
R-squared:	0.294		0.723	

The binary component of the model shows that a low share of foreign demand, low tourism diversity and being rural are common factors across regions with 0 vulnerability (note that the parameters indicate the impact on having vulnerability greater than 0). A possible explanation could be that some demand could have been directed to more isolated regions expecting less demand and less risk of being affected by COVID-19. The fractional component of the model shows the determinants of vulnerability intensity for the 217 regions with a vulnerability score higher than 0. A first evidence is that, controlling for COVID-19 related restrictions, factors affecting destinations' vulnerability are proximal demand, share of foreign tourism, destination type and population density. Vulnerability is lower for destinations with higher proximal demand, which confirms the evidence from Spain (Duro et al., 2021), and for coastal, nature/mountain destinations compared to cities and urban mixed destinations. This seems to indicate that natural assets such as seas, oceans, lakes or mountains keep attracting tourism demand despite the presence of the pandemic. A high share of foreign tourism and a high population density contributed to a higher vulnerability of the destinations, indicating the low preference from tourists of traveling abroad and to crowded destinations during the pandemic.

Conclusions

We proposed a fractional response model to investigate factors affecting destinations' vulnerability. Preliminary results show that, controlling for socio-economic and epidemiological factors, it is possible to identify destination-related characteristics explaining vulnerability. Big data sources were helpful in studying the impact of COVID-19 on tourism demand in 2020, and identifying factors contributing to the destination's vulnerability. Next steps will consider detailed seasonal analysis and the possible inclusion of additional variables, such as tourism density. Future studies are needed to measure the recovery after the demand shock, in order to outline a more comprehensive picture of factors affecting not only destinations' vulnerability but also their capacity to react, as determinant of destinations' resilience.

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