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Covid-19 and tourism vulnerability

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ABSTRACT

The COVID-19 pandemic has dramatically impacted tourism and leisure activities worldwide, especially in the hospitality sector. This paper has a conceptual and empirical motivation based on two objectives. First, it identifies several of the primary factors behind the vulnerability of tourism to COVID-19 (tourism dependency, market structure, the supply of rural accommodation, and health incidence of the pandemic). Second, it constructs a vulnerability index to COVID-19 using Spain and its 50 provinces as case. The main results obtained indicate that tourism to the Balearic Islands, the Canary Islands, the provinces of the Mediterranean coast, and Madrid, in which the state capital is located, present higher vulnerability to COVID-19, yet with different underlying factors. Our methodology and results are of interest to policymakers in terms of the short- and medium-term strategic policies that can be employed to mitigate current and future shocks.

1. Introduction

The COVID-19 pandemic has dealt a severe blow to global tourism and leisure sectors, including the hospitality subsector and its entire value chain. With the seclusion of the population since March (in Europe) and the closure of international borders in many countries, hotel and tourism demand approached zero between April and mid-June, beginning a process (perhaps temporary) of deglobalization (Niewiadomsky, 2020). The fall in the activity will probably be historic (higher than in the 2018 financial crisis) even in a fast recovery scenario around the last quarter of the year. The latest UNWTO forecasts (UNWTO, 2020a) point to various scenarios that see a decrease in international arrivals by 58% and 78%. The socio-economic consequences will be enormous, as tourism is a major economic sector providing livelihoods for hundreds of millions of people.[2]

Spain has a prominent place among the countries affected by the current pandemic. The latest estimates of the IMF indicate the GDP in Spain would contract by around 12.8% in 2020 (IMF, 2020). With a tourism sector accounting for around 12.3% of the Spanish GDP (and 12.7% of employment), a considerable part of the impact would be seen in the tourism sector. In fact, according to Exceltur (2020), half of the expected drop in the country's annual GDP corresponds to tourism, that is, a contraction of almost 44,000 million in foreign currency compared to 2019. However, the impact within Spain is not expected to be evenly distributed. Thus, despite the substantial global and sectoral impact, the results in each territory will vary depending on various specific factors linked to demand (e.g., the weight of the domestic market), supply, or the mitigation and adaptation policies (the emergency response to COVID-19).

This paper addresses the concept of tourism vulnerability to COVID-19 and its measurement through synthetic indices. Although the literature has not unanimously agreed on a definition of vulnerability (Fuchs, Birkmann, & Glade, 2012), there are reasonable approximations to its meaning. For example, according to Turner II et al. (2003) definition, tourism vulnerability is the degree to which a destination is likely to experience harm due to its accidental exposure to risk. Clark et al. (1998) defined vulnerability as a function of two main characteristics: the degree of exposure to the risk and the ability to cope, which includes

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[2] Revenues from tourism could fall by $910 billion to $1.2 trillion in 2020, putting between 100 and 120 million direct tourism jobs at risk (UNWTO, 2020a). To that, one should add jobs in sectors strongly associated with tourism, such as food services, accommodation, entertainment, and retail.

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resistance (the ability to absorb impacts and continue to work) and resilience (or the ability to recover from losses after an impact). However, the multidimensional nature of vulnerability tends to complicate its measurement (Scheyvens & Momsen, 2008).

The applied academic literature related to tourist vulnerability has focused on the effects of terrorist attacks (Liu and Pratt, 2017), climate change (Dogru, Marchio, & Bulut, 2019; Moreno & Becken, 2009; Scott, Hall, & Gössling, 2020), natural disasters (Kim & Marcouiller, 2015), or economic shocks (Gámez, Ivanova, & Campiranon, 2012; Stonich, 2007). In this paper, we analyze vulnerability as related to the current epidemic.

In this respect, COVID-19 has brought about a change in how we think about tourism as academics. Studies used to favor expansion (both in quantitative and qualitative terms), driven by the current globalization process. This way of thought was consistent with the popularization of travel and improvements in transportation and communication technologies (Agnew, 2001). The tourism sector seemed unstoppable despite local and specific episodes related to terrorist attacks, natural disasters, or the 2008 global crisis (Pridaux, Thompson, & Pabel, 2020; Williams, 2009).

However, with the COVID-19 pandemic, the center of attention has moved towards protection and resilience (Prayag, 2020). The current goal is protecting tourism demand as much as possible in a context of high sectoral dependence. As the international demand is at risk, the domestic market has become critical for the tourism season. Thus, the strategic factors have mutated and new ones have come into play.

Given this context, this paper makes three main contributions to the existing literature. First, it reviews some of the main factors behind the concept of vulnerability in the COVID-19 or post-COVID-19 era. These factors are associated with tourism dependence, the density of the accommodation supply, market structure, seasonality, and the pandemic's health incidence (Batista e Silva et al., 2018; Duro, 2016; Gössling, Scott, & Hall, 2020). Second, we propose a synthetic index of tourism vulnerability to COVID-19 based on the previous underlying factors. Synthetic indicators help structure the information of the individual factors in an orderly and reasonable way, obtaining aggregate measures that allow a territorial arrangement. These have already been used to analyze, for example, tourism sustainability (Pulido & Sanchez, 2009) or synthetic competitiveness (Gomez-Vega & Picazo-Tadeo, 2019). Third, we use the proposed framework to study the tourism vulnerability of the Spanish provinces to COVID-19.

As noted earlier, Spain constitutes an interesting case to study because it attracts a large share of international demand, with an enormous weight of the tourism sector in the economy. Furthermore, Spain has been one of the most affected countries by the pandemic, like other traditional European destinations, such as Italy, France, or Germany.[3] The province-level allows us to approximate the destination dimension with the maximum territorial detail. Evidence obtained in our analysis may constitute reasonable support for the design of vulnerability policies in the short and medium terms (Hystad & Keller, 2008).

The paper is organized as follows. Section 2 describes the methodological aspects. The main results obtained are described in Section 3. Further analysis of the results and policy implications are offered in Section 4. Finally, Section 5 summarizes the main results and provides concluding remarks. Additional results are attached in a separate supplement.

2. Data and methods

Indices are based on a plurality of factors, which may help understand the complex, multidimensional characteristics of tourism vulnerability.

The calculation of a synthetic index involves, basically, three decisive phases. First, it is necessary to identify the individual factors. The selection is challenging and often includes subjective decisions. The second important aspect is weighting. The researcher must consider different possibilities, such as non-weighting the indicators or using an exogenous or endogenous weighting methodology. Finally, the third important aspect is that of robustness, as one must study the sensitivity of the results to the choices made in previous steps. In the following sections, we provide details of the methodological steps. A summarizing figure may be found in the supplement.

2.1. Indicator selection, data, and normalization

Indicators for the Tourism Vulnerability Index to COVID-19 (TVI-COVID) must capture both the capacity of the Spanish provinces to protect their tourism market and the relative importance of tourism in the province. The level at which the index is defined makes the selection of indicators a delicate issue, as adequate variables to measure the indicators must be available at the province level. The main dimensions of the vulnerability index and the factors included are fundamentally the following: first, the degree of dependence on tourism (intensity) and density (both positively correlated with vulnerability); second, the role of rural accommodation in terms of global hospitality supply (negative correlation); the role of proximity markets (negative correlation); seasonality (positively correlated), and the health incidence of COVID-19 in the territory (positively correlated). Fig. 1 summarizes these dimensions.

A detailed description of the indicators and the variables employed follows.

- Intensity: A natural factor related to vulnerability is territorial dependence on tourism (Batista e Silva et al., 2018; Gaffney & Eeckels, 2020; Rogerson and Rogerson, 2020). We measure this factor through the total number of overnight stays divided by the province population, given the lack of other variables closer to the tourism activity at the province level.
- Density: Since the COVID-19 has promoted the benefits of social distance, free spaces, and lower density, a factor relative to the number of travelers divided by the province area (in 100 Km^2) has been included.
- Rural Accommodation: Partly related to the previous indicator, rural tourism typically exemplifies a type of demand characterized by little

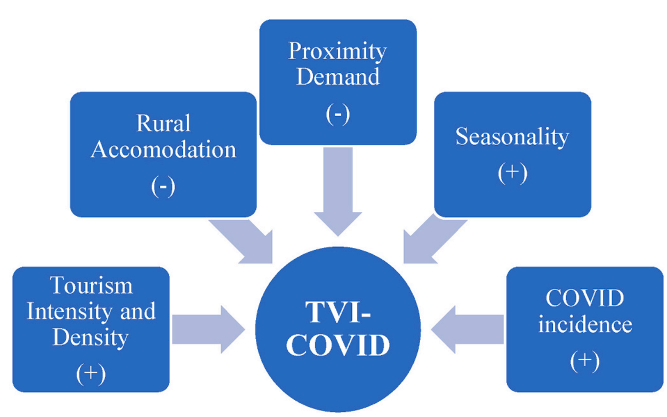

Fig. 1. Dimensions of the TVI-COVID.
Source: own elaboration.

[3] According to data from John Hopkins University (https://coronavirus.jhu.edu/map.html), until December 2020 (at the time the revision of this paper was made), Spain was ranked ninth in the world for both number of infected residents and number of deaths. If compared with the 10 countries that led the ranking of international tourism in 2019, Spain is the second for infection rate (only surpassed by the United States) and the first for mortality rate.

pressure, congestion, and open spaces. The literature has emphasized the benefits of this accommodation supply in the present context (UNWTO, 2020b).[4] We measure rural accommodation by the ratio of overnight stays in rural tourism accommodation to total overnight stays.

- Domestic demand: the interruption of international flows, and their obstacles, revalue in this context the relevance of domestic markets to reduce vulnerability (Gössling et al., 2020; Navarro, Ortega, & Torres, 2020). We employ the relative weight of domestic overnights to measure domestic demand.
- Proximity demand: With similar reasoning, we include the weight of the demand of the international markets closest to Spain in which, among other interesting aspects, the use of the private vehicle for the trip is predominant (the literature justification the same as for Domestic demand). Proximity demand is measured by the weight of the Portuguese and French markets on total global foreign demand (overnights).
- Seasonality: Destinations with a more homogeneous distribution of demand throughout the year may resist better the drop in demand due to COVID-19 (Batista e Silva et al., 2018). The ratio of overnight stays from April to September to total overnight stays has been used to measure seasonality. This indicator is a measure of partial concentration focused on the months in which the effects of the COVID-19 on travel will be higher.
- Incidence: Finally, we use a specific measure of the Incidence of Coronavirus in the province's population as a possibly relevant factor when deciding on the trip destination. We measure Incidence by COVID-19 mortality rates defined as the ratio of the total number of registered deaths in the province as of 1st June 2020 to the total population.[5]

We construct indicators for the Spanish provinces following the definitions above. For.

'Rural accommodation,' 'Domestic demand,' and 'Proximity demand,' we employ the complementary percentages to align all the variables with higher vulnerability.

Our data comes from the National Statistics Institute (INE) for the year 2018 (the latest observation available). The two autonomous cities, Ceuta, and Melilla are excluded from the analysis due to their singular characteristics. A table summarizing all the individual indicators and the variables employed may be found in the supplement.

As the different indicators have different units and ranges, we rescale the variables in a range [0,1] as (min-max):

$$x_{p,i}^{N} = \frac{x_{p,i} - min(x_{p,i})}{max(x_{p,i}) - min(x_{p,i})} \tag{1}$$

where $x_{p,\ i}$ is the value of the i-th individual indicator for the province p.

2.2. PCA and weighting intermediate indicators

We derive weights to aggregate the intermediate indicators following the methodology based on Principal Component Analysis (PCA) developed in Nicoletti, Scarpetta, and Boylaud (2000).

PCA is a multivariate data analysis method aimed for dimensionality reduction, which simplifies the structure of the dataset.[6] PCA makes a linear transformation of the original data into a set of orthogonal variables called principal components. The first component extracts the highest variability (so-called inertia) from the data. The second component is orthogonal to the first and explains the second-highest inertia, and other components are found likewise. If the variables are centered before the analysis (as routinely done), the eigenvalues of the covariance matrix of the data are the variances of the principal dimensions of the (centered) data. The correlations of the components with the variables are called factor loadings. The squared factor loading is the fraction of the variance of the variables explained by the component.

In PCA, only the most informative components are kept. An essential step is, therefore, the decision of the number of components to retain. A standard rule is to keep only components whose corresponding eigenvalues are larger than the average (Kaiser, 1961). This rule collapses to choose components with eigenvalues larger than one if the correlation matrix is employed for PCA. We follow Jackson (1993) and employ a combination of the Kaiser rule and the bootstrapped distribution of eigenvalues to include uncertainty as a part of the decision process.

After the number of components has been determined, factor axes are usually rotated to facilitate the interpretation of the component. As in Nicoletti et al. (2000), we minimize the number of variables heavily loaded in the same component using the Varimax rotation, which delivers new axes that are also orthogonal to each other. However, an oblique rotation may produce a "simpler" structure, allowing factors to be correlated. We also employ an oblique rotation method (Promax) as a robustness check.

PCA has been widely employed to derive weights for composite indicators. Some recent applications in tourism include Santero-Sanchez, Segovia-Pérez, Castro-Nuñez, Figueroa-Domecq, and Talón-Ballestero (2015), Fetscherin and Stephano (2016), Porto, Rucci, Darcy, Garbero, and Almond (2019), or Croes, Ridderstaat, Bąk, and Zientara (2021). PCA-based weights are typically the factor loadings of each indicator on the first principal component. However, the first principal component does not always explain enough variance. Nicoletti et al. (2000) develop a methodology to derive weights from more than one component, which becomes useful in these situations (see, e.g., Gómez-Limón & Riesgo, 2009; Greyling & Tregenna, 2017).

The methodology involves the following steps (see also OECD, 2008):

1. Individual indicators with the highest factor loading on a specific component are grouped into intermediate indices and weighted according to the proportion of their variance explained by the factor with which they are associated (i.e., by the rotated, squared factor loading on that component scaled to unity sum).
2. Finally, the intermediate indices are aggregated into the composite index according to the contribution of the associated factor to the overall variance.

2.3. Robustness

We assess the sensibility of the TVI-COVID some of the discretionary choices made in previous stages. We organize the robustness analysis along three dimensions: PCA sensitivity, model specification, and weighting methodology.

We first analyze if our results are robust to the inclusion of one more component. After, we employ a non-orthogonal rotation of the factors (Promax) instead of the Varimax employed as a benchmark. As there are

[4] In fact, updated data indicates that the percentage of occupation of this type of places is going to approach 100% in Spain this summer. We have also added the Camping accommodation to the rural with no significance change in the results.

[5] We select mortality rates because has attracted more attention in media. The use of other variables, such as the infection rates by province taken from the National sero-epidemiology study of Sars-Cov2 in Spain, lead, virtually, to the same final composite.

[6] See, e.g., Jolliffe (2002) for further details on PCA. PCA techniques are also included in most of the standard multivariate statistics manuals, such as Tabachnick and Fidell (2012).

significant differences in the distribution of intermediate indicators across provinces, we finally analyze the sensitivity of the PCA to the presence of outliers. Outliers may increase (non-robust) measures of covariance, attracting the principal components. To study this potential concern, we conduct robust PCA based on Minimum Covariance Determinant (MCD) covariance matrix estimator (see, e.g., Croux & Haesbroeck, 2000).

Regarding changes in the model specification, we first exclude 'Incidence' from the list of intermediate indicators. The reason for this exclusion is twofold. From one side, it is not clear whether 'Incidence' is exerting a marked influence on destination choices at the province level. Also, 'Incidence' is the only indicator employed that is not fixed in the short-term, as it might vary over time. As a second check, we use average data from 2015 to 2018 to construct the individual indicators (except, 'Incidence') to untie their value from the particular year selected as a benchmark (2018). Finally, we employ a more general vulnerability index not specific to COVID-19. The purpose here is to study if COVID-19 vulnerability is associated with general vulnerability.

For the general index, we exclude 'Incidence' and 'Rural Supply' from the indicators' list because they are COVID-specific. We add a Herfindahl index of foreign market concentration constructed from hotel overnights to reflect the higher risk that a destination entails having an international market concentrated in a few countries. We also change the 'Seasonal' indicator to a more generic version computed with the Gini, as in Duro (2016). With the Gini, we synthetically evaluate the month-on-month inequality in demand rather than looking at the specific months where the COVID-19 is expected to have a higher impact. The hypothesis is that the more uniform the monthly distribution is, the lower the risk the destination has facing local or global shocks. Note that this is a different way from the traditional one in perceiving the problem of seasonality. In this context, seasonality is detrimental in terms of the risk involved.

As a last check, we change the complete weighting method, and we switch from PCA to Data Envelope Analysis (DEA) (Charnes et al., 1978). DEA employs linear programming tools to estimate an efficiency frontier used as a benchmark for the relative performance of the different units (provinces). The method is labeled alternatively as the 'Benefit-of-the-Doubt' when applied to composite indicators.

Within the DEA framework, weights become province-specific and are selected to maximize the province score vis-à-vis all other provinces in the sample. The best performing provinces score one. Underperforming provinces score strictly below one, implying that another province would score higher using the same weights. As we have aligned all indicators towards higher vulnerability, the DEA places each province to its worst (i.e., most vulnerable) scenario. See Cherchye (2001) and Cherchye, Moesen, and Puyenbroeck (2004); Cherchye, Moesen, Rogge, and Puyenbroeck (2007) for further details on the DEA methodology.

The DEA, however, typically leads to many zero weights, as it assigns strictly positive values to (relatively) high indicators only. Several modifications exist in the literature to overcome this concern (see, e.g., Thompson, Singleton Jr, Thrall, & Smith, 1986; Dyson and Thanassoulis, 1988; Allen, Athanassopoulos, Dyson, & Thanassoulis, 1997; Wong & Beasley, 1990; Pedraja-Chaparro, Salinas-Jiménez, & Smith, 1999). In this paper, we follow Wong and Beasley (1990) and complement the DEA with a constrained-DEA version, which allows the province-specific weights to deviate from equally weighting all indices a given percentage π. We set this percentage to 100, 50, and 0% (notice that $\pi = 0\%$ corresponds to equally weighting all individual indicators). González, Cárcaba, and Ventura (2018) contain details on the imposition of the corresponding restrictions.

3. Main results

3.1. The TVI-COVID

We follow the steps explained in the methodological section and run a PCA on the selected indicator variables using the correlation matrix to extract the principal components.

As a PCA pre-test, we evaluate the suitability of the variables using the Kaiser-Meyer-Olkin (KMO) sampling adequacy test and the Bartlett's sphericity test, as typically in the literature. The correlation matrix is provided in the supplement. The KMO value is significantly larger than 0.5 in our data, and Bartlett's test massively rejects the null of orthogonality. Overall, the results of these two testing procedures suggest that the variables are suitable for PCA.

Table 1 summarizes the PCA results. As the table shows, the contribution of the first component is relatively large (50%), but not enough to base the composite index on the first component alone. Therefore, the next step is the selection of the number of components to retain. The joint analysis of this criterion with the bootstrap allows us to consider sampling uncertainty as part of the less-than-one rule.

Table 2 reports the eigenvalues together with their bootstrapped mean, standard deviation, and the 5th and 95th percentiles across 1000 replicas. A scree plot of the eigenvalues with their bootstrapped distribution may be found in the supplement. As Table 2 shows, the first two eigenvalues are larger than one. The 5th percentile range of the bootstrapped distribution of these two first eigenvalues is also over one, indicating that the two principal components must be retained. The third eigenvalue is strictly below one (0.88) but not too far from this number. However, the whole interquartile range of the bootstrapped distribution of the third eigenvalue lies completely below one. Consequently, we retain the first two principal components to derive weights for intermediate indicators. Nevertheless, we examine the robustness of the resulting weighting scheme to include one more component (Section 3.4).

The selected two components jointly explain 70% of the variability, with a residual sum of squares (RESS) of 2.16 (30%). Fig. 2 reports Q and Hoteling's T^2 statistics to assess the quality of the selected model. The Q statistic measures how well an observation matches the model. As the figure shows, Balearic Islands presents a relatively larger Q statistic than the other provinces, but we do not find anomalously high residual-outliers. We obtain similar findings with the T^2. This statistic allows the detection of provinces with large scores, which may strongly influence the principal components. As the bottom plot in Fig. 2 shows, no province presents a severe T^2, but the statistic is higher for Balearics and Las Palmas (one of the Canary Islands provinces). These two provinces present considerably larger values for most of the indicators. Consequently, we analyze the robustness of our findings to the presence of outliers in the corresponding section (Section 3.4).

Once the components have been selected and the quality of the model assessed, we derive weights for intermediate indices from the first two components as in Nicoletti et al. (2000). Table 3 shows the

Table 1
Eigenvalues of the individual indicators. PC—principal component.

PC.	Eigenvalue	Proportion of Variance	Cumulative Proportion
1	3.50	0.50	0.50
2	1.34	0.20	0.70
3	0.87	0.12	0.82
4	0.56	0.08	0.90
5	0.48	0.07	0.96
6	0.17	0.02	0.99
7	0.08	0.01	1.00
KMO measure of sampling adequacy	0.73		
Bartlett's test of sphericity	χ^2=193.77	df = 21	$p < 0.0000$

Source: own elaboration.

Table 2
Selected bootstrapped eigenvalue results.

Eigenvalue	Mean	Std.	5th - 95th percentiles
3.50	3.58	0.93	[2.25; 5.28]
1.34	1.35	0.22	[1.01; 1.73]
0.87	0.82	0.15	[0.58; 1.07]
0.56	0.53	0.09	[0.39; 0.68]
0.48	0.36	0.08	[0.22; 0.49]
0.17	0.14	0.04	[0.08; 0.21]
0.08	0.06	0.02	[0.03; 0.09]

Notes: Results based on 1000 bootstrapped replicas.
Source: own elaboration.

(varimax-rotated) factor loadings of the two components. The indicators with the highest factor loadings on the first component are 'Intensity' (0.74), 'Density' (0.92), 'Rural Tourism' (0.61), 'Domestic demand (0.95)', and 'Proximity demand (0.76)'. On the contrary, 'Seasonality' and 'Incidence' present higher loadings on the second component (0.78 and − 0.72, respectively). Table 3 also contains the squared factor loadings (scaled to unity sum), which measure the proportion of the variance of the factor explained by each of the individual indicators.

Following Nicoletti et al. (2000), we group indicators according to the factor with which they are mostly associated (in bold in Table 3) and use normalized squared loadings to aggregate them after into intermediate composite indices. Finally, we summarize the intermediate indexes into the composite in a proportion of the explained variance of the factor (i.e., 68% for the first factor and 32% for the second).

The final implicit weights obtained for each indicator are provided in the last column of Table 3. As the table shows, the PCA methodology gives slightly more weight to 'Density' and 'Domestic demand' indicators, as they have a stronger weight on the most important factor. However, we do not find large discrepancies across indicators weights, with percentages not far from those obtained equally weighting all components (14%).

The resulting TVI-COVID index is presented in Figs. 3 and 4. Fig. 3 depicts the score of each province in the composite index. As we have rescaled indicators to [0,1], scoring one would require the highest value in all individual indicators. Fig. 4 maps the 50 provinces by their TVI-COVID score ranking. Provinces shadowed with a darker color in the map highlight higher tourism vulnerability to COVID-19. A table summarizing both scores and the province ranking is provided in the supplement (Table S.2). The supplement also provides a table with the province scores in each of the individual indicators (Table S.3), which may help to characterize the distribution of provinces across individual indicators.

The Balearic Islands emerge as the most vulnerable province. In this case, the bulk of vulnerability factors place this province in an awkward position. With a high dependence on tourism in its GDP, it is the province with the highest seasonality in Spain (Duro, 2016) and high weight in the international market (basically, Germans and English). The vulnerability situation also reaches the Canary Islands, which are strongly dependent on tourism, although, in this case, seasonality works in their favor.

The vulnerability ranking is also very high for the province of Barcelona, due to the enormous exposure of the capital, strongly dependent, for example, on international markets. The high density also plays a significant role in explaining this ranking. Different destinations on the Mediterranean coast are also added to the previous list of provinces. In

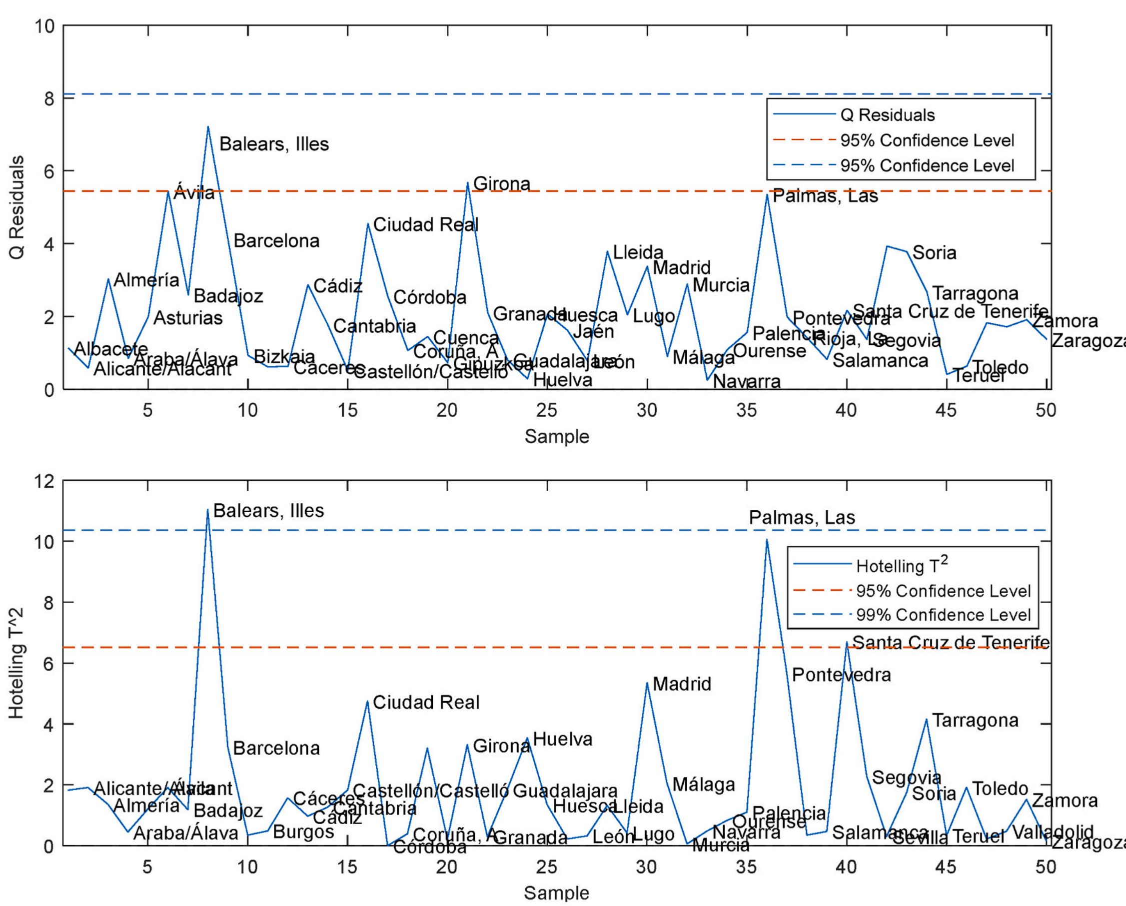

Fig. 2. Q and Hoteling's T2 statistics.
Notes: Residuals account for 30% of the variability.
Source: own elaboration.

Table 3
Rotated factor loadings used in the calculation of weights.

	Factor 1		Factor 2		Implicit Weights
	Factor loadings	Squared loadings, scaled to unit sum	Factor loadings	Squared loadings, scaled to unit sum	
Intensity	**0.74**	0.17	0.28	0.05	13%
Density	**0.92**	0.26	0.10	0.01	19%
Rural Tour.	**0.61**	0.11	0.41	0.11	8%
Domestic D.	**0.95**	0.27	0.19	0.02	21%
Proximity D.	**0.76**	0.18	−0.31	0.06	13%
Seasonality	−0.04	0.00	**0.78**	0.40	14%
Incidence	−0.24	0.02	**−0.72**	0.34	12%
Exp. Var	3.31		1.53		
Exp./Tot	68%		32%		

Notes: The table shows varimax rotated loadings. Exp. Var is the variance explained by the factor. Exp./Tot is the explained variance divided by the total variance of the two factors. Squared loadings are scaled to the unity sum. Implicit weights are the final weights for each indicator in the TVI-COVID.
Source: own elaboration.

this way, the vulnerability concentrates on the Mediterranean coast plus the province where the State capital, Madrid, is located. Therefore, it seems that the islands, Mediterranean coast, and largest capitals dimensions are behind vulnerability. Contrary, the lowest tourism vulnerability areas are the bulk of the interior areas and heritage capitals. We characterize with more detail the distribution of the scores across provinces in the following section.

3.2. Taxonomy of TVI-COVID scores across provinces

To characterize differences in TVI-COVID across provinces, we compare the scores by a set of geographic, climatic, demographic, and economic groups. We assess differences in vulnerability by geographic groups (‘Coast’ vs. ‘Inland,’ and ‘Mediterranean’ vs. ‘non-Mediterranean’), the province climate (‘Dry’ vs. ‘Temperate’), the population size of the province’ capital (‘Large capital’ vs. ‘Small capital’), and the GDP per capita (‘High gdppc’ vs. ‘Low gdppc’)).

Coast locations include provinces with Mediterranean, Atlantic, or Cantabric shores. The set of provinces with Mediterranean shores is also employed to define the second geographic group. Climatic classification is defined using Köpen and corresponds to the province capital. Provinces with large capital population-size correspond to provinces with capitals with a population exceeding 200,000 inhabitants. Finally, (relatively) high GDP per capita indicates that the province GDP per capita is above the national average.

We obtain the data to form the groups from the INE database, except for the climate group, which comes from the State Meteorological Agency (AEMET). The observation year is 2018, which is also the date used for individual indicators.

Fig. 5 depicts the average values of the TVI-COVID between the two groups defined by each of the four aggregations. The Figure shows that, on average, coast provinces are more vulnerable than inland, primarily the Mediterranean. The dry climate also seems to be positively associated with vulnerability. Besides, provinces with large capital-size have, on average, a substantially larger score. The average scores do not differ much across GDP per capita groups, albeit they are slightly higher for more prosperous provinces.

To determine if the observed differences are significant, we perform a two-sample *t*-test on equal means in all groups (Welch's t-test). We summarize the results of the testing procedure in Table 4.

As the table shows, the differences in average scores between the location (the two classifications) and city-size groups are massively significant. For the climatic groups, the statistical evidence is weaker yet still significant at 10%. As expected from Fig. 3, we cannot reject the null of an equal average between groups defined by GDP per capita at any usual significance level. The result reveals the lack of association between the *ex-ante* distribution of GDP per capita and tourism vulnerability. The correlation coefficient between the composite index scores and the per capita GDP is relatively low (0.17).

However, note that the restrictions to mobility generated by the alarm state are producing severe damage to the economy, which is more acute for specific sectors, such as tourism. Consequently, the TVI-COVID is likely associated with the ex-post distribution of labor market outcomes. More specifically, with the change of employment before and after the pandemic. We explore this issue in the following section.

3.3. TVI-COVID and labor market deterioration

The outbreak of COVID-19 has impacted the Spanish labor market strongly, bringing labor statistics to unprecedented values in the historical series. For example, the average registration in social security decreased by 548,100 people in April 2020, and the cumulative impact by the end of that month is estimated to be around 1,200,000 fewer taxpayers (Garcia and Ulloa, 2020). The fall in employment per se does not provide a full picture of the situation because it does not account for temporary layoffs. The Spanish Government has given preference to temporary regulation over dismissal, facilitating firms to adopt

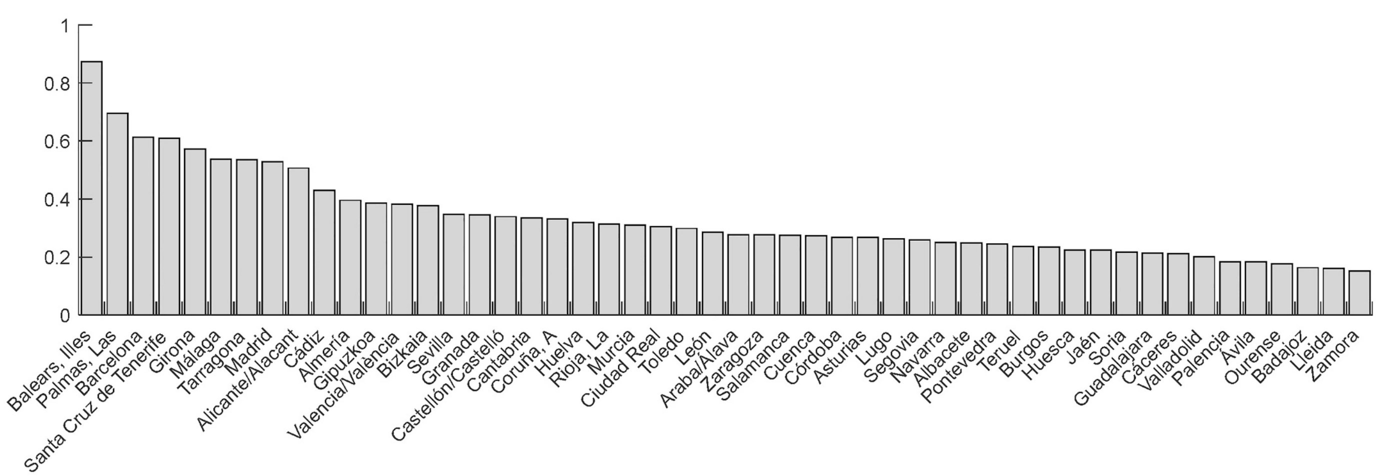

Fig. 3. The TVI-COVID for the Spanish provinces.
Source: own elaboration.

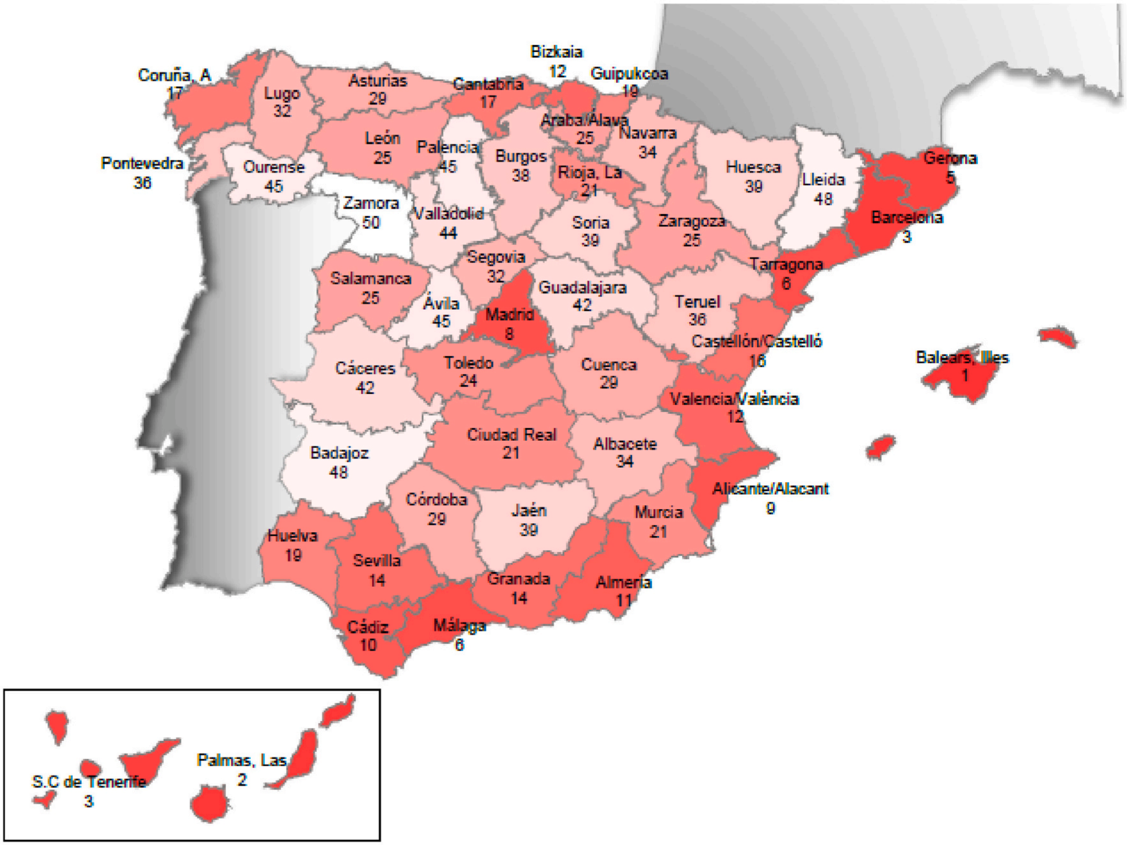

Fig. 4. The Spanish provincial map of TVI-COVID for the Spanish provinces.
Notes: Numbers in the Figure are the province score ranking in the TVI-COVID. Darker areas highlight higher vulnerability.
Source: Own elaboration.

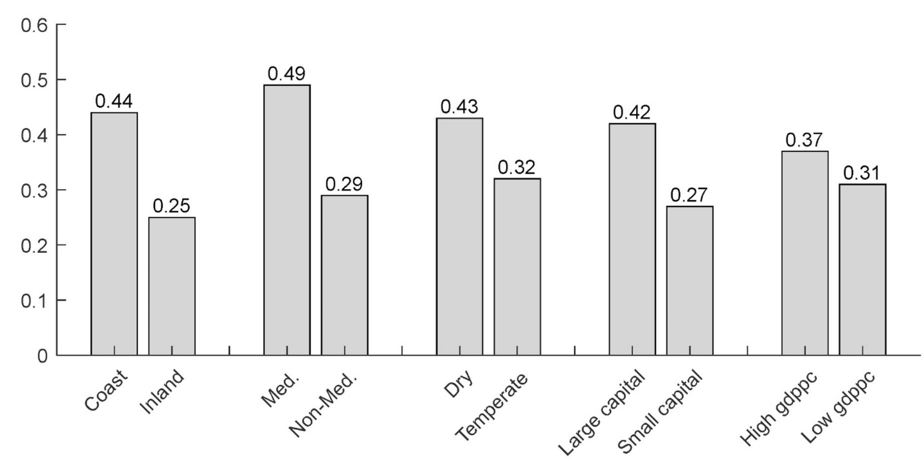

Fig. 5. TVI-COVID scores by different groups of provinces.
Notes: Average index scores between different groups.
Source: own elaboration.

Temporary Redundancy Plans (ERTE). As a result, the number of persons affected by force majeure ERTE, which were utterly marginal before the alarm state, rose to over 3,000,000 by the end of April.

This section investigates the relationship between the TVI-COVID and the labor market deterioration generated by the pandemic. We expect the association to be positive, as tourism concentrates most of the employment deterioration and ERTEs in Spain. For example, according to Social Security data released by Turespaña, an agency under the Spanish Ministry of Industry, Commerce and Tourism, the Spanish tourism sector accounted for half of the fall in Social Security registration in May 2020, and has about1,000,000 employments subjected to a force majeure ERTE. Consequently, if the index signals tourism vulnerability to COVID-19 correctly, the pandemic should have crippled the labor market stronger in provinces presenting high scores in tourism vulnerability.

We estimate by OLS two versions of the following equation, where ε_i is a zero-mean and constant-variance error-term:

Table 4
Test on equal population means.

	Location				Climate		City-size		GDPPC	
	Coast	Inland	Med.	Non-Med.	Dry	Temp.	Large capital	Small capital	High gdppc	Low gdppc
Average	0.44	0.25	0.49	0.29	0.43	0.32	0.42	0.27	0.37	0.31
t-statistic	4.91		3.85		1.63		3.05		1.18	
p-val	0.00		0.00		0.10		0.01		0.24	

Notes: The test does not assume equal variances in the two populations.
Source: own elaboration.

$$Y_i = \beta_0 + \beta_1 TVI - COVID_i + \varepsilon_i \tag{2}$$

In the first specification, the dependent variable is the (year to year) relative change in employment from 20th April 2019 to 20th April 2020. In the second version, we consider the ratio of workers affected by force majeure ERTE to the total social security affiliates (also for 20th April 2020.) The data used to build the dependent variables is obtained from the INE, and the two dependent variables are measured in per-unit terms.

Estimation results for the two model specifications are provided in Table 5 and Fig. 6. As the table shows, the estimated slope coefficients are massively significant. The linear model predicts a decrease of 0.6 percentage points in the number of affiliates for each additional 0.1 points in the vulnerability score (recall the TVI-COVID lies in the [0,1] interval, and dependent variables are defined in per-unit terms). Likewise, the same increase of 0.1 points implies an increase in ERTE of 2.2 percentage points.

However, the most striking result is the large R-squared, especially when the dependent is the proportion of ERTE. This result implies that the TVI-COVID index alone can explain a large portion of the variability in the proportion of ERTES across provinces (more than 50%). Notice that any individual indicators employed in constructing the TVI-COVID index contain labor market information (or other economic). More importantly, they are constructed using data from the year 2018, thus before the pandemic. The only exception is 'Incidence,' which uses mortality rates as of 1st June 2020. However, as explained in the following section (Robustness), the exclusion of Incidence does not alter the vulnerability index. In particular, the estimation of the two previous equations remains unaltered when we do not use 'Incidence' to construct the composite index (supplement, Table S.6).

Table 5
OLS regression of TVI-COVID on labor market deterioration.

Specification 1: Dependent isΔ % Employment

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	−0.019091	0.005353	−3.566619	0.0008
TVI-COVID	−0.063506	0.014651	−4.334689	0.0001
R-squared	0.281324	F-statistic		18.78952
Adjusted R-squared	0.266352	Prob(F-statistic)		0.000074

Specification 2: Dependent is %ERTE

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	0.077776	0.010379	7.493358	0.0000
TVI-COVID	0.227280	0.028409	8.000304	0.0000
R-squared	0.571447	F-statistic		64.00487
Adjusted R-squared	0.562519	Prob(F-statistic)		0.000000

Notes: Δ % Employment – relative change in employment (Social Security registration) between 20th April 2020 and the same date, previous year; % ERTE – percentage change in ERTE over total employment on 20th April 2020.
Source: own elaboration.

Overall, the regression analysis provides a good test of the explanatory power of the TVI-COVID. Overall, the results from the previous two regression points towards the index have the power to predict the most vulnerable areas. Therefore, it can be employed as an advanced indicator of the tourism resilience to COVID-19 of the Spanish provinces.[7]

3.4. Robustness analysis

In this section, we provide the analysis of the robustness exercises explained in Section 2.3. These checks will allow us to assess whether the results discussed in the previous section are robust to some of the discretionary choices made in the construction of the TVI-COVID. Selected results from all robustness checks are summarized in Table 6. The table provides the Spearman rank correlation coefficient between the composite index in the robustness checks and the benchmark (BM). The closer the coefficient to one, the closer the two rank provinces. The detailed province's rankings are provided as supplementary material to conserve space.

We organize the discussion as follows. We first study the sensitivity of the PCA method to the number of components, the rotation method, and the presence of outliers. After, we assess possible changes in the province ranking due to changes in the model specification. Finally, we obtain weights for intermediate indicators using the DEA method instead of the PCA.

The first three columns of Table 6 summarize the results from the first three sensitivity checks. As the table shows, neither including an additional component (SENS1) nor using Promax rotation (SENS2) significantly alter the province rankings, so the Spearman correlations are large. The classification of provinces is also robust to the possible presence of outliers (SENS3).

Finally, we check the robustness of the province ranking obtained to changes in the weighting methodology itself. Results are summarized in the last four columns of Table 6. Column seven reports the results with the standard (unconstrained) DEA. The results obtained with the constrained DEA versions (C-DEA), which allow province-specific weights to deviate a maximum of 100, 50, and 0% from equal weighting, are reported in the last three columns. As expected, the rank obtained with the DEA is the one that presents the most considerable discrepancies with the BM. Notice that the DEA leads to many zero weights for intermediate factors by construction. This can make a province score higher in the vulnerability ranking so that it is a priory challenging to justify.[8] However, the discrepancies are not large, and the Spearman rank correlation between the two indices is, in any case, very high.

Overall, the results of this section highlight the robustness of the classification of provinces obtained with the TVI-COVID index.

[7] At the time of writing this paper, the 2020 summer results were not still available. However, they have become available during the revision process. The supplement contains the regression of percentage fall in 2020 summer tourism hotel demand with respect 2019 on the TVI-COVID (Table S.5 in the supplement). Correlation between the index and the percentage fall in summer hotel demand is large (0.8), implying that the index alone explains 64% of the variance in the percentage fall in overnight stays across provinces.

[8] Table S.7 in the supplement contains the weights obtained using the DEA method. An interesting example is Ciudad Real, which presents the higher incidence among all provinces. This makes this province to score one with the DEA, while is 23rd in the BM, when compensation is possible (Table S.8.c, in the supplement).

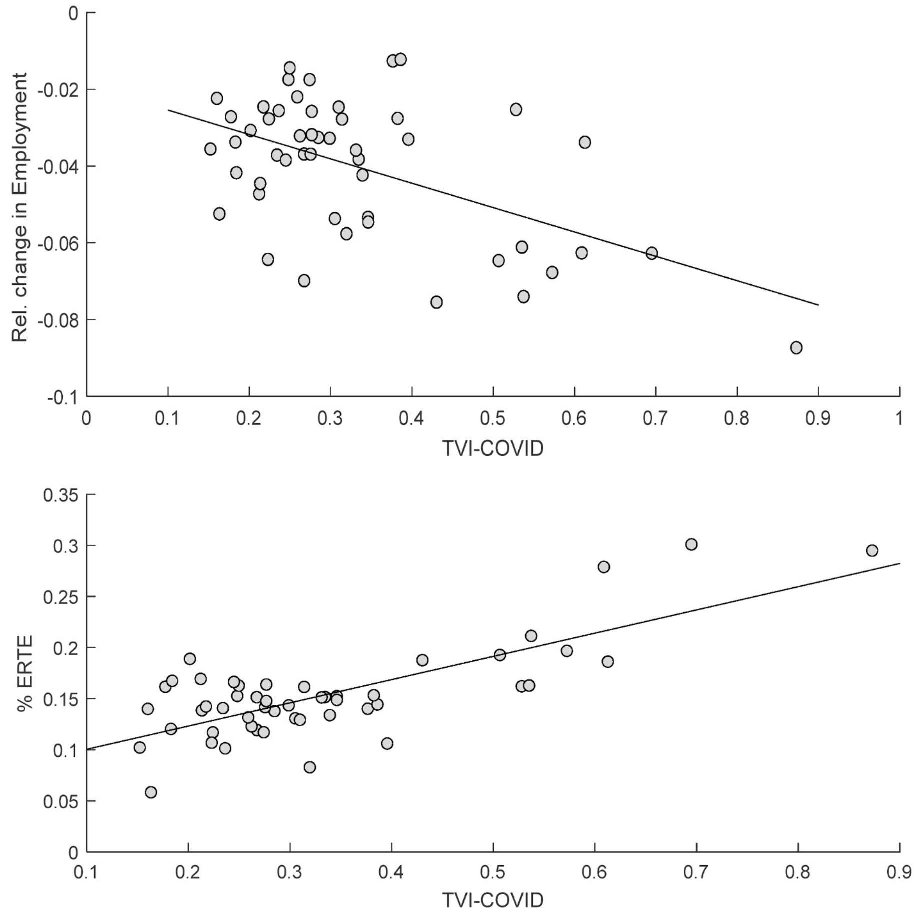

Fig. 6. Scatter plot: TVI-COVID and labor market deterioration.
Source: own elaboration.

Table 6
Spearman correlation.

PCA					
SENS1	SENS2	SENS3	SPEC1	SPEC2	SPEC3
0.99	0.99	0.95	0.95	0.99	0.92
DEA and C-DEA					
	DEA	$\pi = 100$	$\pi = 50$	$\pi = 0$	
	0.82	0.97	0.98	0.99	

Notes: The table shows the Spearman correlation between the index obtained in the corresponding robustness check and the benchmark index. SENS1: three PC; SENS2: Promax rotation; SENS3: PCA based on robust MCD estimator; SPEC1: incidence' excluded from indicators' list; SPEC2: average 2015–2018 data used to construct indicators; SPEC3: general tourism vulnerability index; C-DEA: constrained DEA version, allowing deviations of $\pi = 100$, 50, and 0% maximum from equally weighting all indicators (0% corresponds to equal-weighting).

4. Discussion

The enormous impact of COVID-19 on the Spanish hospitality, tourism, and leisure sectors, together with the weight this sector has on the Spanish economy, will likely induce a historic crisis, even if the pandemic recedes. Our proposed vulnerability index constructed for the Spanish provinces illustrates the different positioning of these territories, suggesting that the effect of the crisis can be asymmetrical. We stress the importance of indicators related to sector intensity and density, the weight of the domestic market, the weight of the closest international markets, the amount of rural accommodation supply, tourism seasonality, and the incidence of the pandemic itself. Thus, despite the global problem, better positions in previous factors reduce the magnitude of the impact. Our index, built on seven factors, is representative and robust to different aggregation methodologies and factors. More importantly, we have shown that it is strongly correlated with the actual evolution of employment given the latest available data.

The results suggest that the Balearic Islands, the Canary Islands, the provinces where the two great state capitals are located (Barcelona and Madrid), and various provinces on the Mediterranean coast lead the ranking of tourism vulnerability. In each case, the combination of factors that determine the index may differ (see Table S2 in the supplement for more details).

Starting with the Balearic Islands, its greatest vulnerability might be attributed to a toxic combination of all factors. The tourism density in the Balearic Islands is the highest among the Spanish provinces, and the province also scores extremely high in intensity. At the same time, the domestic market has the lowest weight, and the relative importance of the closest international markets is minimal. Moreover, the rural tourism supply in the Balearic Islands is scarce, and seasonality is exceptionally high and concentrated in the months with the most significant COVID-19 impact.

According to our index, the Canary provinces (Las Palmas and Santa Cruz de Tenerife) also present high vulnerability. In the Canary case, the main factors behind vulnerability are the high density, intensity, and low weight of the domestic and proximity international markets. However, seasonality is not the problem, contrary to the Balearic case. The sun-and-beach product is present in the ranking, likewise, by the two Catalan provinces located to the north and to the south, that is, Girona and Tarragona. Above all, seasonality is also the main factor behind their high vulnerability score (jointly with the intensity factor).

The provinces containing the two largest cities (Madrid and Barcelona) also present a high vulnerability to COVID-19. The high density, lower weight of the domestic and proximity international markets, low rural tourism supply, and the high incidence are behind their TVI-COVID score.

Overall, we observed that factors previously considered positive, such as a high and diverse international activity, become penalized in the presence of COVID-19. In contrast, the provinces with lower scores are generally inland territories, with low density, low tourism dependence, and high weight of the domestic market in its demand structure. The group tests performed indicate that being a coastal province, especially in the Mediterranean, being in a dry area, and containing a large city are characteristics that favor tourism vulnerability.

The immediate question that emerges is how our results can be used for mitigation policies in the short- and medium-term future. Solving tourism vulnerability in the short-term is complicated, but the above factors, the results obtained, and the current situation suggest reasonable mitigation strategies for the future.

First, a great lesson from COVID-19 is how crucial the domestic market is to reducing risk and vulnerability. Until now, in our view of endless growth and economic impact, it had been quite reviled in the face of the advantages of international markets (i.e., the farther, the better). Nowadays, however, we remember the fundamental contribution of nearby markets to maintain the demand. In the absence of international demand, the promotional campaigns focus on this segment (Hall, Scott, & Gössling, 2020). The domestic market, however, should not be the object of attention in the current situation only. If we must learn something, it is the need to minimize risk, and the domestic market is central within this strategy (Gössling et al., 2020).

Second, the importance of proximity has also made us examine the closest international markets: tourists that are within driving distance. For the case of Spain, these are Portuguese and French tourists. Like with the domestic market, the prominent strategy in the past was instead to diversify international markets and differentially attract distant markets.

Third, the rural tourism supply (e.g., accommodation services) seems to emerge as the least affected by the current crisis given its competitive factors (lower density, free spaces). Therefore, it should also receive more attention from public policy in the future.

Fourth, the fight against seasonality emerges as an attractive policy, not only in terms of environmental, social, or economic sustainability but also in risk diversification. Seasonality was one of the main imbalances of destinations given that it produced negative consequences in terms of economic efficiency (Getz & Nielson, 2004), environmental sustainability (Lusseau & Higham, 2004), labor (Ashworth & Thomas, 1999), or social (Kuvan & Akan, 2005). With the COVID-19 pandemic, seasonality appears to us as an important problem in terms of the inherent risk. Having the bulk of the demand over a few months implies a huge potential risk, as problems in the markets may also concentrate in these months, as with COVID-19. The reduction of seasonality and the progress towards a more homogeneous monthly distribution is required to reduce these risks.

Finally, the current situation offers the opportunity to focus on tourism intensity to re-think tourism on different and more sustainable bases. Some authors, such as Romagosa (2020), have recently addressed this issue as possible learning from COVID-19. Strategies of territorial fluffing of the product and lowering density would be consistent with less vulnerability. Some authors have traced the future recovery phase to transform the current production processes (Pridaux et al., 2020). Perhaps, following Niewiadomsky (2020), it could be the opportunity for a restart (or a reset) rather than a "return to normality." However, this strategy appears unrealistic in the short-term, as governments will likely focus on recovering as many jobs as possible to reduce the high unemployment rates generated by the pandemic (Hall et al., 2020).

5. Concluding remarks

In this work, we have investigated the vulnerability of tourism associated with the COVID-19 pandemic. Our attention has been primarily focused on two issues: first, a conceptual one, which is linked to identifying several reasonable and measurable factors associated with vulnerability; second, proposing a composite vulnerability index. This index aims to synthesize a multidimensional element into a single scalar, which has forced us to use several aggregation methodologies well-established in the literature.

We have analyzed tourism vulnerability to COVID-19 for the case of Spain and its 50 provinces. Spain is an interesting case to study, as it is both is a country highly specialized in tourism and one of the most affected economies by the pandemic. The territorial choice (province), on the other hand, has allowed us to explore the territorial dimension of the crisis.

We have identified a set of factors behind tourism vulnerability related to COVID-19 dictated by parsimony, representativeness, and data availability. These factors are related to tourism intensity and density, the supply of rural accommodation, market structure, seasonality, and pandemic incidence. The selected indicators have been aggregated with the help of factors extracted from PCA, which has allowed us to assess the relative position of the Spanish provinces. We have studied the sensibility of the proposed TVI-COVID index based on several robustness checks, which have not significantly altered the province vulnerability rankings. Our results show that the islands (Balearic and Canary), the Mediterranean coast (including Barcelona), and Madrid are the most vulnerable. Moreover, we have shown that the indicator correlates with recent unemployment increases induced by the pandemic. As most of the tourism sector concentrates most of these layoffs, it is, therefore, to be expected that tourism to these provinces (Balearic, Canarias, Madrid, and Barcelona) is likely going to be the most affected by COVID-19 in the summer of 2020.

In the paper, we have stressed that the current obsession with vulnerability and risk reduction has changed our assessment of several underlying factors. This is the case, for example, for both domestic (nowadays receiving special attention) and the closest international markets. We have also shown that the vulnerability to COVID-19 is primarily connected to global tourism vulnerability. Tourism destinations must take steps to reduce their risks and vulnerability since it seems inevitable that the sector will again be affected by shocks. The risk for future shocks significantly changes the strategic context in the medium and long terms. The COVID-19 crisis has shown that strategies focused on tourism intensity are exposed. Consequently, this model (crowded and unsustainable) is structurally vulnerable.

Future research must analyze whether the vulnerability factors stressed in this work (intensity, density, incidence, seasonality, rural supply, and domestic and proximity demand) explain differences in tourism demand resilience across Spanish provinces when data becomes available from the summer of 2020. An analysis of other countries/regions would also help investigate if our findings can be extended to other regions. We find these questions exciting avenues for future research.

Credit author statement

J.A.Duro, A.Pérez-Laborda and M.Fernández have contributed to the conceptualization, methodology, investigation and writing of the paper. A. Pérez-Laborda, in addition, has been the responsible for the main formal analyses. J.Turrión has contributed to investigation.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tmp.2021.100819.

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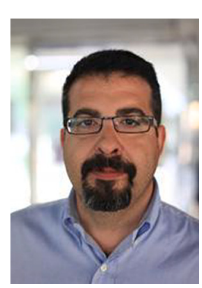

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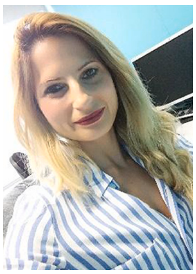

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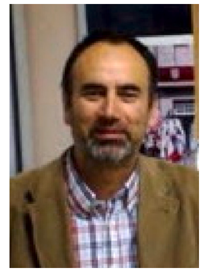

Melchor Fernández is a Professor of Economic Theory at the University of Santiago de Compostela (Spain) and the former director of the Research Institute of Development Studies of Galicia (IDEGA). His lines of research are particularly focused on labour market topics, as well as, regional development and economy-wide models applied to tourism. In 2009, Melchor's research was awarded with the *Lluis Fina Award* for the best paper in the Spanish Labor Conference. Moreover, his research has included projects for the Spanish Government, the Galician Regional Government and the Galician Tourism Studies Institute.