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Measuring tourism markets vulnerability across destinations using composite indexes

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ABSTRACT

This paper addresses the concept of tourism vulnerability associated with the structure of the destinations' tourism source markets, by using several relevant factors and the construction of synthetic indexes. Following an operable and parsimonious criterion, we select a reduced set of fundamental indicators that have been stressed in the literature, and that are related to dimensions such as the destination proximity, the degree of the market demand concentration, the strength of seasonality, or the economic profile of the tourists. We implement this framework for the fifty Spanish provinces, using hotel travelers as an indicator of the demand for a destination. In this way, we guarantee a wide territorial coverage and heterogeneity of factors. The results obtained withstand various robustness analyses, and indicate that the play of the various factors means that among the most vulnerable provinces there are all kinds, both specialized in sun and beach, and urban, cultural or rural, for example (which indicates that the tourism model does not determine the degree of vulnerability). On the other hand, the vulnerability would be associated with the magnitude of the demand and would have little to do with the competitiveness measures as they have been proposed up to now. Overall, the proposed methodology and empirical results can be easily applied in practice and are of great interest for researchers, managers and policymakers.

1. Introduction

Until the Covid-19, the bulk of the academic profession, policymakers, and tourism stakeholders believed in the infinite expansion of the tourism sector (Pridaux et al., 2020; Williams, 2009). Forecasts indicated demand increases, boosted by middle-class income growth in emerging countries and transportation facilities. However, the current pandemic has crudely brought reality back, making it clear that the type of growth that destinations were facing was fragile.

Several authors have highlighted that tourism activity is exposed to shocks that jeopardize the sector given that is an open system (Ridderstaat & Nijkamp, 2016; Ritchie, 2004; Williams & Bálaz, 2016). Although several definitions of vulnerability exist from different areas of knowledge, it is usually associated with a greater probability that an unanticipated event significantly affects the sector's activity, such as the occurrence of an adverse natural phenomenon (Paraskevas & Altinay, 2013). Clark et al. (1998) and Turner II et al. (2003) not only consider the probability of external events but also include in the definition of vulnerability the ability to manage and adapt to these unforeseen impacts. Furthermore, they also consider the ability to manage changes in the demand caused by partially controllable events, such as population aging, changes in lifestyle and consumption patterns, or environmental concerns, which destinations must address to achieve long-term tourism sustainability.

In fact, the risk and vulnerability has been dimensions traditionally forgotten in the theoretical concept of Tourism Destination Competitiveness (TDC) and the empirical applications using different indicators leading to popular country or destination rankings. On this regard, it is expected that a competitive destination should be able to convert their advantageous position into economic returns (Abreu-Novais, Ruhanen, & Arcodia, 2015; Li et al., 2013). However, for instance, the tourist demand dynamics during the years of the pandemic for different countries collected in the UNWTO World Tourism Barometer (UNWTO, 2022) shows that countries traditionally classified as highly

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competitive, have presented a significant decrease in international tourism flows in 2020 in comparison to 2019. In this context, it might seem that, despite the trend in the literature to increase the number of variables to be included in the TDC empirical applications (Dwyer et al., 2003; Hallmann et al., 2014; Shariffuddin et al., 2022), the concept of risk had been clearly neglected.

So far, literature has mainly considered vulnerability to four general types of events. (1) Most studies analyze the vulnerability of tourism to natural disasters and other environmental shocks, especially those driven by the (differential) effects of climate change (Cioccio & Michael, 2007; Dogru, Marchio, & Bulut, 2019; Moreno & Becken, 2009; Becken & Santana-Gallego, 2020; Scott et al., 2019). (2) Some other studies address the vulnerability of destinations to wars and other episodes of political conflict (e.g. Enders & Sandler, 1992; Fourie et al., 2019; Liu & Pratt, 2017; Mansfeld, 1999). (3) Since the income elasticity of tourism is high compared to other goods, the literature also considers the effect of crisis and other economic shocks that impact on income (Perles et al., 2016; Pridaux et al., 2003; Ritchie, 2004; Williams & Bálaz, 2016). (4) Finally, a last stream of the literature has analyzed the eventuality of epidemic episodes, including the recent Covid-19 pandemic (e.g. Duro et al., 2021; Gössling, Scott, & Hall, 2020; Hall et al., 2020; Kreiner & Ram, 2020; Miller & Ritchie, 2003).

In this paper, we address the vulnerability that comes from the structure of the destination (demand) source markets. Notice that in previous studies, the emphasis was placed on the phenomenon that destinations managers could not control, such as a natural disaster. Our approach in this paper is different. We address the *ex-ante* vulnerability associated with the structure of a destination demand, for which the destination managers can have some *ex-ante* partial control. We consider that looking at vulnerability from this perspective is of great interest, because the structure of the source market is crucial and determines the heterogeneous response of the different destinations to uncontrollable external effects. In our view, an essential part of the weakness of the current tourism growth model is generated by the structure of the source market, which is a fundamental component of the tourism overall vulnerability (the overall vulnerability may include other elements such as tourism dependency or climate change). Therefore, the vulnerability associated with the distribution of the tourism source markets goes well beyond pandemics or other short-run vulnerabilities and is better placed in the medium-run.

For example, concentration of the source market is likely to be an essential factor for the destination vulnerability. If the concentration is large, the *ex-ante* vulnerability that the destination faces (before being hit by any shock) is high as there are fewer substitute demand sources available in the event of a shock (Gallego & Font, 2019). Notice, however, that concentration does not distinguish between source markets. But some source markets are likely to be more vulnerable than others. Therefore, it is necessary to identify the different factors behind the complex nature of vulnerability and measure it through a composite index.

This paper intends to identify a set of factors (as being: few, reasonable, understandable, and measurable) and synthesize all their information in a single composite indicator. In addition to concentration, which is positively associated with market vulnerability, we consider other factors that have to do with the proximity of the destination to the source markets, the seasonality, or the income profile of the demand. Nearby demand source markets, among which the domestic market plays a crucial role, have emerged during COVID-19 as true escape valves in the face of the virtual evaporation of the international flow of tourists due to the pandemic restrictions on mobility (Duro, Osório, & Perez-Laborda, 2022; Gössling et al., 2020; Navarro-Jurado et al., 2020). This issue is even more crucial when considering that the international flow of tourists account for the bulk of the global tourism (WTTC, 2018). Seasonality, which refers to the temporal concentration of flows (Duro, 2016), has also been seen as a problem for vulnerability, since the concentration of the touristic flows occurs on specific months that can be affected by various type of shocks (Batista e Silva et al., 2018; Calgaro et al., 2014). Given the multidimensional nature of vulnerability of the touristic destinations, we summarize all this information through a composite index. This composite index helps us obtain a broad vision of the vulnerability of a destination in terms of its source markets and its inherent risks and allows us to make comparisons between touristic destinations in terms of vulnerability.

We believe that the development of single indicators of vulnerability can be very useful for policymakers and destination managers. First, they highlight the nature of tourism vulnerability considering simple, operational and rigorous market structure indicators in a useful way at a global level. Second, given that vulnerability is a multidimensional concept it requires composite indexes (Pena, 1994), as a tool for synthesizing information, facilitating the interpretation process in a context of multidimensionality and of variety of indicators and, therefore, of complexity. In fact, this methodology can be generally used by other studies and in other contexts. Thus, composite indexes seem to be cost-effective measures that maximizes information utility (Atauri et al., 2002). Finally, those indexes provide an analytical framework for monitoring and better decision-making by stakeholders and policymakers in order to evaluate the results of their policies and, therefore, increase the resilience of tourism destinations (Calgaro et al., 2014).

We empirically apply the previous framework for the fifty Spanish provinces (NUTS 3). The selection of Spain is due to its worldwide importance as a recipient of tourists (UWWTO, 2020), and the availability of homogeneous data for the representative indicators of the different dimensions of market vulnerability. The analysis at the province level brings us closer to the characteristics and profile of each destination than a more aggregated analysis. In turn, the number of provinces available (fifty) favors the exploration of vulnerability in a context of heterogeneity, which eases the statistical analysis. The destinations demand data refers to hotel travelers. Consequently, with the available indicators of market vulnerability for the different provinces, we derive a composite indicator that allows the provinces to be ordered in terms of market vulnerability and to test several hypotheses. For instance, we address whether the resulting vulnerability classification is somehow related with the notion of tourism competitiveness highlighted, for example, by the World Economic Forum. We also study whether vulnerability is related with resilience, among other aspects.

In this context, policymakers require clear, transparent, and operational indicators to continuously monitor the situation and to make decisions (White et al., 2006). Thus, the vulnerability indicator proposed in this paper, together with any other associated indicator (or indicators) must be part of the portfolio of strategic targets and information from which destination managers and policymakers based their decisions and policies. The COVID-19 pandemic made clear the importance and necessity of using vulnerability indicators. Therefore, in our perspective the proposed composite index can be an important tool for destination management, by reflecting (part of) the multidimensional nature of vulnerability (Pena, 1994). In this sense, vulnerability indexes may act as alert systems that can help policymakers and destination managers make better strategic decisions and reduce risk.

The paper is organized as follows. Section 2 discusses the factors behind markets vulnerability, and Section 3 the methodological issues behind the construction of the synthetic index. The results are reported in Section 4. Then, Section 5 discusses the results and highlights their implications. Finally, Section 6 makes the concluding remarks.

2. Indicators of market vulnerability

Renewed interest in tourism vulnerability has led researchers attempting to measure this concept in order to make it operational. However, since vulnerability is a complex phenomenon, these approaches must consider various factors to capture its multidimensional nature. For example, the UNWTO *tourism dashboard* classifies countries based on three factors: the weight of tourism in the country's GDP, the importance of the international market, and the weight of tourism exports. Thus, this classification considers two critical aspects of tourism vulnerability: tourism dependence and the weight of international flows (distance). Tourism dependence is also considered by Gallego and Font (2019) to analyze the vulnerability of tourism destinations to the availability of air transportation.

This paper aims to construct a composite index of the destinations tourism market vulnerability (TMV) using the 50 Spanish provinces (NUTS 3) as territorial units for the analysis. In this context, we must find indicators of market vulnerability that are readily available at the province level of aggregation and easily understood. This aspect is extremely important because, we want to construct an index for which the data is readily available and that is operationally easy to apply in practice by destination managers and policy makers. Atauri et al. (2002) recommended a parsimony approach and noted that basing the composite index on a reduced set of indicators increases its practical use. Following on this recommendation and restricted by the availability of data at the province level, we establish the TMV index on six fundamental indicators that we believe can capture the complexity of tourism markets vulnerability to a great extent, with all the necessary caveats.

The first three indicators considered are related to the geographical distance. (Müller, 1998; Ridderstaat and Nijkamp, 2016; Smeral, 2009). In this respect, the weight of the domestic source market has been massively highlighted in the academic literature as one factor of vulnerability mitigation. Lower importance of the domestic market (with respect to the international market), exposes destinations more widely to international shocks, making them more vulnerable (Arbulú et al., 2021; Barrot et al., 2016; Duro, Pérez-Laborda, & Fernández-Fernández, 2022; Gnangnon, 2016). Authors such as Gössling et al. (2020), Navarro-Jurado et al. (2020), Phuc and Dinh (2020), have recently highlighted the role of the domestic market in increasing the resilience of tourism destinations during the COVID-19 pandemic.

However, the distinction of markets in terms of distance based only the domestic vs. international dichotomy would be incomplete. In this context, we note that some international markets are less likely to lead to vulnerabilities than others because they are closer to the destination or because they have strong links of mutual knowledge and exchange (Duro et al., 2021). In this sense, we highlight the importance of nearby international markets, which for Spain are France and Portugal. Tourism coming from nearby countries is less vulnerable than tourism coming from distant countries because travelers can get to the destination more easily, by road, typically private car, thus being less dependent on air-transportation. As noted in Gallego and Font (2019), dependence on air-transportation increases the strategic risks, threatening the resilience of destinations. Likewise, we also consider the weight of remote international markets situated outside the EU, which typically having a significant economic impact. However, non-EU markets are more vulnerable than the EU markets because they are less accessible and are subject to different regulations, which can act as an additional barrier to travel in the event of a shock (Batista e Silva et al., 2018; Calgaro et al., 2014; Duro et al., 2021; Koo et al., 2016).

The source market concentration is another factor behind the destinations' tourism vulnerability (Bull & Weed, 1999; Sharpley, 2003). Concentration is an indicator of exposure typically found in the economics, industrial organization and marketing literature. In this context, note that no matter the distance, concentrating the international demand in a reduced set of countries increases exposure because there are few substitution possibilities available, which creates a situation of low demand diversity, making the destination more vulnerable (Gallego & Font, 2019).

Like concentration, seasonality also increases vulnerability (Batista e Silva et al., 2018; Duro et al., 2021; Koo et al., 2016). The hypothesis is that a greater concentration increases the destination likelihood and exposition to shocks, because there would be less chances of reversing the effect of the shock if that would happen in the months where demand is concentrated (Koo et al., 2016). The argument is analogous to that of market concentration, but in this case using a temporal (monthly) approach. In this sense, an indicator that would be consistent with this conceptualization would be the inequality indicator, such as the well-known coefficient of variation (Cowell, 1995).

Finally, the last indicator considered is the income profile of the demand. The idea here is that wealthier tourists resist better the impact of economic shocks than lower income tourists.[1] This issue has become evident during the COVID-19 pandemic in Spain. Consequently, specialization in the high-income profile makes the destination less vulnerable. Fig. 1 summarizes the previous six dimensions.

Nevertheless, we have to underline that The list of factors included are related to those suggested by the literature and adapted to the general availability of data at the territorial level in any country (as being: few, reasonable, understandable, and measurable). Thus, other factors could have been also hypothetically considered if they were available. For example, the age structure of tourists, and in particular, the weight of senior tourism, which theoretically may be more vulnerable to the bulk of possible shocks (such as the COVID-19 pandemic).

3. Data and methods

After the individual dimensions behind each of the complex phenomenon discussed before having been identified, the calculation of the composite index proposed in this paper involves two steps. First, we need to obtain the variables that measure the individual indicators. Second, we must consider how to aggregate these individual factors into the final composite index. As these steps involve subjective decisions, it is also important to analyze (ex-post) the sensitivity of the final composite index to the choices made.

3.1. Variable selection, data, and normalization

Following the previous discussion, we consider a set of sufficiently consistent variables for the different dimensions, which are summarized in Fig. 1. In this context, we focus on travelers to hotel establishments

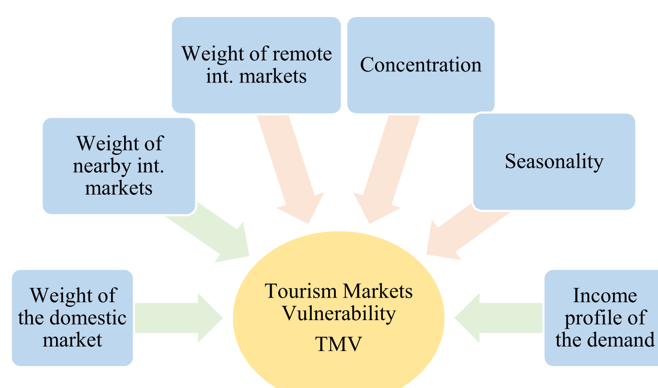


Fig. 1. Dimensions of the TMV index. Notes: Red (green) arrows indicate a positive (negative) association with markets vulnerability. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)
source: own elaboration.

[1] The measurement used to capture the profile is partial and very approximate. Thus, particular incomes and also wealth position can influence the tourism demand Ridderstaat (2021a, 2021b). However, the variable used has the advantage of being intuitive and operational in most international statistical systems. Moreover, this simplicity allows greater and applicability of the proposed methodology and synthetic indexes in general.

only. On the one hand, we use travelers as the decision unit because they are more relevant than overnights since we are more concerned on markets and management. On the other hand, hotel establishments are the most critical component of the tourism demand in all provinces, having a considerably more significant economic impact than other establishments. Besides, travelers to hotel establishments data is available at the province level, while data for other components, such as camping, cannot be found for all provinces. The information is obtained from the 2019 Hotel Occupation Survey, which is monthly carried out by the Instituto Nacional de Estadística of Spain (INE). We employ data from 2019 in order to avoid the effect of the COVID-19 pandemic, which may otherwise induce reverse causality to our indicators.

Table 1 summarizes the individual indicators considered, their definition, and their relationship with market vulnerability. Specifically, the weight of the domestic market is defined as the ratio of the hotel domestic travelers to the total hotel travelers. Likewise, the weights of the nearby and international demand source markets are defined, respectively, as the ratios of hotel travelers from France and Portugal and from non-UE countries with respect to the total international travelers. As for market concentration, we employ the Herfindahl index. This index is a widely accepted measure of concentration calculated by squaring each country's share in the destination total number of international hotel travelers and summing up the resulting numbers. Higher values of the Herfindahl index are associated with higher concentration and, thus, higher vulnerability. Seasonality is measured by the coefficient of variation of monthly hotel demand, as in Duro (2016). The coefficient of variation is a standardized measure of relative dispersion. The higher the coefficient, the more seasonal and vulnerable the destination. Finally, in the absence of a better indicator at the aggregation level, the income profile is measured as the percentage number of travelers to 4 and 5-star hotel establishments.

We re-scale the variables in a range [0,1] (min-max) to make the indicators comparable and align them towards higher vulnerability.[2] Fig. 2 plots a heatmap for each indicator. Darker areas highlight vulnerable provinces. The precise scores for each province are reported in Table A1 in the Appendix.

As the figure shows, there is substantial variation in the distribution of market vulnerability indicators across provinces. For instance, the Balearic Islands emerge as highly vulnerable in most of them. According to each indicator, the most vulnerable provinces are the Balearic Islands for the weight of the domestic and nearby source markets, Madrid for the importance of remote source markets, Alicante for the source market concentration index, the Balearic Islands once more for seasonality, and Teruel for the income profile of the demand. Conversely, the less vulnerable provinces are Soria, Lleida, Las Palmas de G.C., Albacete, and S.C. de Tenerife for the last two indicators.

To disentangle patterns in the distribution of individual indicators across territories, we compare the average scores by a set of geographic, demographic and economic groups. Precisely, we assess average differences by two types of geographic groups ('Coast' vs. 'Inland,' and 'Mediterranean' vs. 'non-Mediterranean'), by the population size of the province' capital ('Large' vs. 'Small'), and by the GDP per capita ('High' vs. 'Low'). In particular, coastal provinces include those with Mediterranean, Atlantic, or Cantabrian coastlines. The set of provinces with Mediterranean shores is also used to define the second geographic group. Provinces with large capital cities correspond to provinces with capitals with more than 200,000 inhabitants. Finally, the high (relative) GDP per capita group gathers provinces with GDP per capita higher than the national average. Results are provided in Table 2, including a two-sample Welsh test on equal means to determine significance.

As Table 2 shows, coastal provinces are on average more vulnerable than inland provinces according to the weight of the domestic market, nearby markets, concentration, and seasonality, and less vulnerable according to the importance of distant markets and the income profile. However, the significance of the difference cannot be established for concentration at standard levels. A similar pattern holds for the Mediterranean vs. non-Mediterranean group. On average, a large capital city is related with province that are more vulnerable according to the three distance and concentration indicators and less vulnerable for seasonality and income. Nevertheless, the statistical significance of the difference between groups is sometimes weak. Finally, more prosperous provinces tend to be less vulnerable according to nearby and distant markets and more vulnerable according to the remaining four indicators. However, the difference between the 'High' and 'Low' GDP groups is not significant, except for the weight of nearby markets.

Table 1
Indicators of tourism markets vulnerability.

Individual Indicators	Variable Definition	Direction
Weight of domestic market (DOM)	% Domestic hotel travelers.	NEG
Weight of nearby markets (NEAR)	% French and Portuguese on int. hotel travelers.	NEG
Weight of remote markets (REM)	% Non-UE on int. hotel travelers.	POS
Concentration (CONC)	Herfindahl Index of int. hotel travelers.	POS
Seasonality (SEAS)	Coefficient of monthly yearly variation.	POS
Income profile (INC)	% Travelers to 4&5 stars hotels.	NEG

Notes: All the variables are based on 2019 data to avoid the effect of the COVID-19 pandemic.
source: own elaboration.

3.2. Weighting individual indicators

We aggregate individual indicators in a unique dimension to construct the final composite index. Aggregation usually involves the calculation of a weighted arithmetic mean of individual indicators I_k, $k = 1 \ldots K$:

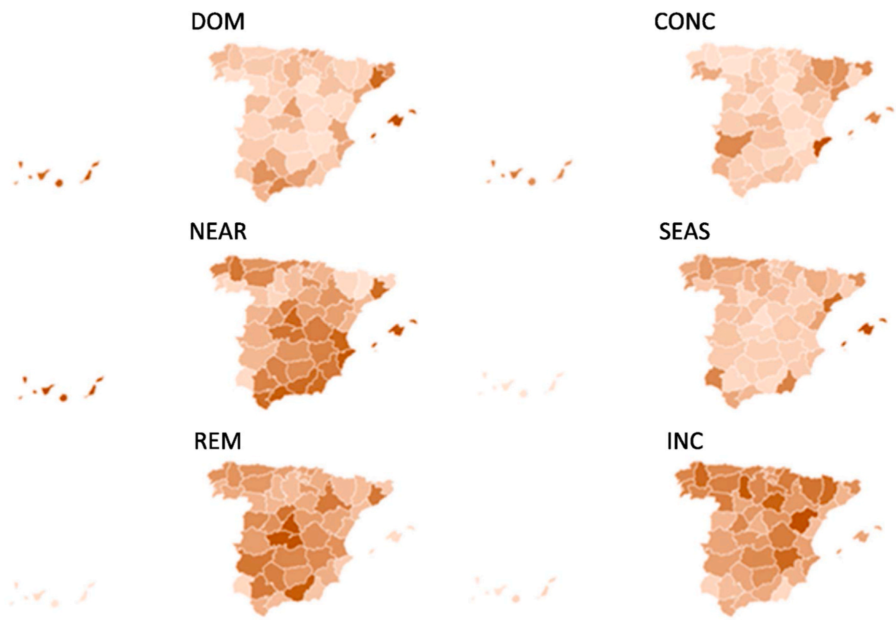
$$VTM_i = 100 \times \sum_k w_k I_i^k.$$

The weighted average requires deciding the weight w_k of each indicator. To do so, we employ a data-driven methodology to overcome the concerns associated with any subjective direct weighting. In addition, the use of a data-driven method also counteracts discretionary decisions made at other stages of the composite index's construction (Blancas et al., 2013).

In this paper, we derive weights for the individual indicators by extracting them from Principal Component Analysis (PCA), as in Gómez-Limón and Riesgo (2009), Santero-Sanchez et al. (2015), Greyling and Tregenna (2017), or Duro et al. (2021). In summary, the methodology uses PCA to form a composite index that captures a large portion of the variance common to the individual indicators. PCA is a multivariate method that reduces the dimensionality of the dataset by linearly transforming the original data into a set of orthogonal variables, known as principal components (Jolliffe, 2002). The first component extracts the data's highest variability. The second component is orthogonal to the first and accounts for the second-highest variability. The other components are obtained in the same way. As variables are centered before PCA, the eigenvalues of the covariance matrix of the data are the variances accounted for by the principal components.

When applying PCA as a weighting technique, the standard method uses the factor loadings on the first component (Klasen, 2000). However, the first principal component often fails to capture a significant portion

[2] The min-max transforms is $I_i = \frac{X_i - \min(X)}{\max(x) - \min(x)}$, which lies between f and one. Indicators negatively associated with vulnerability are oriented towards higher vulnerability as $I_i' = 1 - I_i$.



Notes: All indicators are re-scaled to [0,1] and aligned towards higher vulnerability. Darker areas signal more vulnerable territories—source: own elaboration.

Fig. 2. Individual indicators of market vulnerability across Spanish provinces. Notes: All indicators are re-scaled to [0,1] and aligned towards higher vulnerability. Darker areas signal more vulnerable territories.
source: own elaboration.

Table 2
Average indicator values across different groups.

		DOM	NEAR	REM	CONC	SEAS	INC	VTM
Location	Coastal	0.451	0.662	0.391	0.311	0.410	0.454	44.714
	Inland	0.190	0.473	0.572	0.212	0.228	0.648	39.867
	pval $\mu_1 = \mu_2$	0.000	0.021	0.007	0.151	0.006	0.002	0.047
	Mediterranean.	0.496	0.720	0.400	0.352	0.437	0.410	46.820
	Non-Med.	0.245	0.504	0.521	0.226	0.267	0.611	40.478
	pval $\mu_1 = \mu_2$	0.009	0.034	0.156	0.190	0.081	0.001	0.067
Capital	Large	0.568	0.818	0.505	0.310	0.224	0.415	48.633
	Small	0.222	0.473	0.488	0.239	0.335	0.609	39.905
	pval $\mu_1 = \mu_2$	0.001	0.000	0.864	0.454	0.195	0.001	0.005
GDPpc.	High	0.379	0.417	0.441	0.304	0.355	0.596	42.251
	Low	0.267	0.628	0.518	0.231	0.284	0.546	41.871
	pval $\mu_1 = \mu_2$	0.146	0.018	0.271	0.293	0.323	0.423	0.893

Notes: Values in the table are the average inside groups. The p-value corresponds to a Welsh *t*-test of equal means, which does not assume equal variances in the two populations.
source: own elaboration.

of the overall variance. Nicoletti et al. (2000) developed a method to overcome this problem. The technique consists of the following steps. First, factors are extracted from the principal components kept for analysis. Next, the associated factor loadings are rotated (typically using Varimax) to produce a more straightforward structure with fewer indicators heavily loaded on the same factor. After that, the indicators having the highest loading on the same factor are grouped and aggregated into intermediate indexes, weighted by the percentage of the indicator variance accounted for by the factor with which they are associated. Finally, these intermediate indexes are aggregated into the final composite index weighted by the factor's contribution to the overall explained variance. Further details on the method can be obtained in the OECD *Handbook on Constructing Composite Indicators* (OECD, 2008).

We follow the previous steps to determine weights for the TMV index. As a preliminary stage, we standardize the variables (z-score) and use the Kaiser-Meyer-Olkin (KMO) sampling adequacy test and the Bartlett's sphericity test to assess the suitability, as it is typically in the literature. The KMO value is significantly greater than 0.5, and Bartlett's test massively rejects the null of orthogonality. Overall, the results of these two procedures indicate that the variables are appropriate for PCA. Table 3 summarizes the PCA results. The first and second columns of the

Table 3
Eigenvalues of the individual indicators.

PC.	Eigenvalue	Proportion of Variance	Cumulative Proportion	Bootstrapped Median and Interquartile Range
1	2.18	0.36	0.36	2.37 [2.08; 2.73]
2	1.76	0.29	0.66	1.60 [1.41; 1.78]
3	0.81	0.13	0.79	0.80 [0.69; 0.89]
4	0.55	0.09	0.88	0.49 [0.43; 0.55]
5	0.40	0.07	0.95	0.43 [0.29; 0.37]
6	0.30	0.05	1.00	0.21 [0.17; 0.25]
KMO measure of sampling adequacy 0.68				
Bartlett's test of sphericity p-val < 0.0000				

Notes: Bootstrap results are obtained with 1000 bootstrap replicas.
source: own elaboration.

table report the principal component and their associated eigenvalue. The proportion of the total variance explained by each component is written in column three, and the cumulative proportion up to a given component is in column four.

As the table shows, the contribution of the first component is not high enough to base weighting on it alone (36%). Therefore, the next step is selecting the number of components to retain. A general rule keeps only components with eigenvalues greater than one (Kaiser, 1961). To incorporate uncertainty into the decision process, we follow Jackson (1993) and use a combination of the Kaiser rule and the bootstrapped distribution of eigenvalues. The last column of Table 3 shows the mean and interquartile range of the bootstrapped distribution of eigenvalues across 1000 replicas. As Table 2 shows, the first two eigenvalues are larger than one, but the third is strictly less than one (0.81). Furthermore, the entire interquartile range of the bootstrapped distribution of the third eigenvalue is significantly lower than one. Following this evidence, we keep the first two principal components to calculate weights for intermediate indicators, which jointly explain 66% of the total variability.

After the number of retained components has been determined, axes are usually rotated to facilitate the interpretation of the component. As in Nicoletti et al. (2000), we use the Varimax rotation to create a more precise loadings pattern, which allows us to identify the factor with which variables have the strongest association. The rotated factor loadings of the two extracted components are shown in Table 4. As the data has been demeaned and scaled to unit variance before PCA (z-score), the loadings are just the correlations between the components and the indicators. As the Table 4 shows, the first two distance indicators ('DOM' and 'NEAR') and the income profile of the market ('INC') heavily load on the first rotated factor (the correlations are 0.88, 0.72, and −0.78, respectively). In turn, the weight of remote markets, market concentration, and seasonality have higher loadings on the second factor (0.85, −0.67, and −0.69).

Table 4 also includes the squared factor loadings (scaled to unity sum), which quantify the share of the variable variance explained by each rotated factor. Following Nicoletti et al. (2000), we group indicators according to the factor with which they are most associated (in bold) and aggregate the indicators within each group into intermediate indexes according to the squared correlation with the factor with which they are associated. After, the resultant two intermediate indexes are combined into a final composite in a proportion of the explained variance of each factor (52% and 48% for the first and second factors, respectively). The implicit weights for each indicator resulting from this aggregation are shown in the last column of Table 4. As the table shows, the methodology gives slightly more weight to the weight of the domestic and distant source markets (21% each) and less to the income profile of the demand (13%). However, there are no significant differences in weights. A robustness check of the weighting methodology is carried out in the corresponding section (Section 4.3).

Table 4
Rotated factor loadings and implicit weights.

	Factor loadings		Squared factor loadings scaled to unit sum		Weights for VTM
	F1	F2	F1	F2	
DOM	0.86	−0.20	**0.36**	0.02	**21%**
NEAR	0.72	0.43	**0.25**	0.10	**15%**
REM	−0.12	0.85	0.01	**0.39**	**21%**
CONC	0.35	−0.67	0.06	**0.23**	**17%**
SEAS	−0.17	−0.69	0.01	**0.25**	**14%**
INC	−0.78	0.14	**0.30**	0.01	**13%**
Exp.Var.			2.05	1.90	
Exp/Tot.Exp			0.52	0.48	

Notes: The table shows varimax rotated loadings. Exp.Var is the variance explained by the factor. Exp./Tot.Exp 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.
source: own elaboration.

4. Tourism market vulnerability across Spanish Provinces

4.1. The TMV index

We employ the weights obtained in Table 4 to aggregate individual factors into the final composite index. Selected results are presented in Fig. 3, which maps the 50 provinces by their score. Provinces shadowed with a darker color in the map highlight provinces with a higher vulnerability of tourism markets. The specific score of each province in the VTM index is presented in Table A1 in the Appendix.

The Balearics emerge as the province with the most vulnerable markets. As noticed before, many factors collapse in this province (see Table A1 in the Appendix). Balearics has the lowest percentage of domestic tourism among all provinces and very low importance of nearby tourism. It is also the most seasonal, with virtually all travelers concentrated during the summer months. The only low vulnerability indicator for Balearics is the weight of remote markets, as most of its tourism comes from UE. Barcelona scores the second higher according to the vulnerability of its tourism markets, followed by Granada, Madrid, Toledo, and Alicante. These provinces present high vulnerability according to the first three vulnerability indicators. The exception is Alicante, which presents low vulnerability according to markets distance, but has its tourism concentrated in few countries (mainly British and German). Huelva, Valladolid, Castellon, Zamora, and Orense situate on the other side of the spectrum. In general, they all show very low scores in most individual indicators of vulnerability.

We investigate the taxonomy of the TMV index by computing average scores among the different groups considered for individual indicators (i.e., coast vs. inland, the Mediterranean vs. non-Mediterranean, large vs. small capital cities, and rich vs. poor). Results from this analysis are also presented in Table 2. As the table shows, higher index values tend to be associated with coastal provinces, mainly the Mediterranean, and a highly populated capital. It is also associated with higher per capita GDP, although the statistical evidence of the latter result is weak.

Notice, however, that, despite statistical significance, the differences in TMV average scores across pairs are much narrower than those observed using individual indicators. As explained in Section 2, the reason is that individual indicators do not necessarily signal the same territories. For example, coastal provinces are on average more vulnerable than inland if we focus on the importance of the domestic and nearby markets and tend to present higher concentration and seasonality. However, coastal provinces are less vulnerable than inland provinces if one considers the importance of the remote international markets and the income profile of the demand (See Table 1). Likewise, provinces with highly populated capitals are on average more vulnerable according to the three distance indicators and market concentration but are less vulnerable according to seasonality and income profile. Disagreement among individual indicators is crucial as it implies that their information is not redundant. The TMV index aggregates all the available information, and, as a result, the province scores become much more destination-specific. Notice that the taxonomy of vulnerable provinces is considerably more diverse than that of individual indicators. For instance, among the ten most vulnerable provinces, there are both interior and coastal, with high and low populated capital, and with high and low per capita GDP. The same result emerges if one concentrates on the ten least vulnerable.

4.2. Relationship with other variables

This section studies how the proposed index relates to some variables of interest. We start by testing the explanatory power of the VTM index, assessing its relationship with the distribution of 2020 hotels resilience

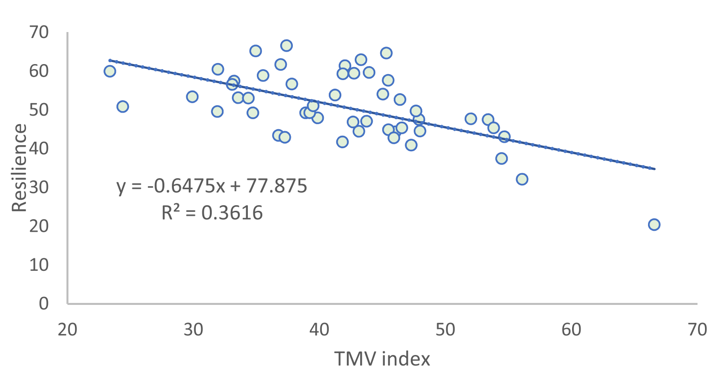
Notes: Darker areas highlight vulnerability - source: own elaboration.

Fig. 3. TMV index scores across Spanish provinces. Notes: Darker areas highlight vulnerability.
source: own elaboration.

to the COVID-19 Pandemic across Spanish provinces. The VTM is not meant to be an indicator of vulnerability to COVID-19, as for example, it does not consider incidence data. The VTM is meant to be a general indicator of vulnerability. However, we expect a strong, negative association with resilience as it signals the most vulnerable markets. To investigate this issue, we measure 2020 resilience as the fraction of the average 2015–2019 hotel demand that the province retained in 2020:

$$res = 100 \times \frac{hotel\ demand_{2020}}{av.(hotel\ demand)_{2015-2019}}$$

Results are presented in Fig. 4, which depicts the scatter plot of 2020 hotel resilience on the proposed index, together with the regression line. As expected, there is a significant negative association between the two variables. Thus, provinces with a less vulnerable market in 2020 secured a substantially higher fraction of their hotel demand. Moreover, the relationship between the two variables is strong. The correlation coefficient is −0.62, implying that the market vulnerability can explain around 40% of their hotel demand resilience variance. Note that this is a high percentage for a single explanatory variable in a regression, especially considering that the VTM index is constructed from 2019 data, that is, before the spread of the COVID-19 Pandemic. Thus, our results have causal interpretation in Granger terms (Granger, 1969). On



Notes: 2020 hotel resilience is measured as the fraction of the average 2015-2019 hotel demand that the province retained in 2020. Source. Own elaboration

Fig. 4. Relationship between the TMV index and COVID-19 hotel resilience Notes: 2020 hotel resilience is measured as the fraction of the average 2015–2019 hotel demand that the province retained in 2020.
Source. Own elaboration.

average, scoring 1 point more in the index in 2019 implies that the change in the number of travelers to the 2015–19 average is 0.65% lower. Overall, the strong, negative association shows that the VTM index has strong power to predict vulnerable markets.

After assessing the predictive power of the vulnerability index and its relationship with the resilience of the Spanish provinces, we investigate how the distribution of the VTM relates to intensity, as measured by the total number of travelers. Fig. 5 plots the scatter plot of the 2019 (log) number of hotel travelers on the proposed VTM index. The figure shows a strong, positive association between the two variables (the correlation coefficient is 0.60). On average, scoring one point more in the vulnerability index is associated with 7% more travelers in the province.

Unlike in Fig. 4, the relationship shown in Fig. 5 is not necessarily causal. However, it highlights a problematic association between the two variables: destinations with more vulnerable markets are precisely those of higher demand or in which tourism is more massified. Thus, consistent with recent evidence from the COVID-19 crisis, the vulnerability of the tourism market of the leading Spanish destinations puts in check not only the tourism sector but also the entire economy, given that tourism is one of the cornerstones of the Spanish economy and an outstanding driver of economic growth and social development (tourism account around 12,4% of Spanish GDP in 2019 and sustained around 12,7% of employment. *Spanish Tourism Satellite Account*. INE).

The results in Fig. 5 also suggest that the vulnerability of tourism markets does not conform to tourism competitiveness, as defined, for example, by the World Economic Forum (WEF, 2019) . Unfortunately, there are no competitiveness indexes available in Spain at the provincial level. They are, however, at a regional level (NUTS 2, CCAA) provided by Exceltur (Exceltur, 2019). Therefore, we dig further into this issue by analyzing the relationship between the proposed index and Competitiveness at regional level. To do so, we construct indicators for the individual factors in Table 1 using 2019 data for the 17 Spanish regions, and we employ the PCA weights in Table 1 to build the VTM index at the regional level. Table A2 in the Appendix reports the specific scores for each region. The Appendix also provides a figure mapping the distribution of the VTM index at the regional level. Overall, the resulting regional distribution is consistent with that found at the province level, with Balearic Islands, Madrid, and Catalonia having the most vulnerable markets according to the composite index.

Fig. 6 depicts the scatter plot of Competitiveness on the VTM. As the figure shows, we find a positive association between Competitiveness and market vulnerability. Thus, on average, territories scoring the highest in competitiveness score, the higher they are in terms of market vulnerability. Again, we do not claim the result is causal. However, the strong positive association between the two indexes suggests the need to revise the concept of Competitiveness to include indicators of exposure and vulnerability.

4.3. Robustness analysis

In this section, we perform a sensitivity analysis of the VTM index to evaluate the robustness of the evidence provided above. As a first check, we analyze the sensitivity of the PCA-based weights to outliers. Outliers may increase (non-robust) covariance matrix estimations, attracting the principal components. Therefore, we recompute the weights using a robust PCA version based on the Minimum Covariance Determinant (MCD) covariance matrix estimator, as in Croux and Haesbroeck (2000). The resulting composite index is denoted as RB1.

Second, we assess the sensitivity of the VTM index to the weighting methodology itself. We switch from PCA-based weights to equally weighting all individual factors (RB2) to do this check. Using symmetric weights for all indicators is often regarded as a reasonable option when there is a lack of direct evaluative information on the importance of each dimension (Gallego and Font, 2019; Torres-Delgado & Palomeque, 2018). Finally, we changed the definition of some of the variables used for the individual factors. Specifically, we redefine the weight of the nearby and remote markets, making them relative to the total number of travelers instead of to international travelers only. We also changed the seasonal indicator to a version computed with the Gini (see, e.g., Duro, 2016). Once the new variables were constructed, we followed the same steps in Section 2 to derive a third version of the composite index (RB3).

The result from these robustness checks is summarized in Table 5. The table provides the implicit weights used in constructing the alternative indexes and their (Spearman) rank correlation of scores with the original VTM. The closer the rank correlation to one, the closer the alternative and the original VTM rank the provinces. The detailed index values are provided in the Appendix to conserve space.

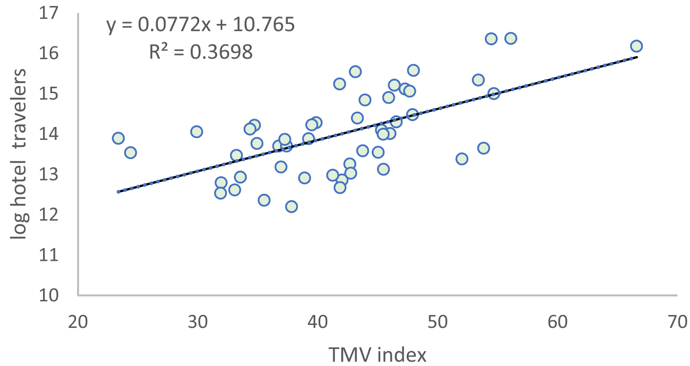
As the table shows, the results offered are not sensitive to possible outliers. The weights obtained with the robust PCA version do not differ much from the original VTM index (in Table 3). Comparing the two sets of weights shows that the domestic market's importance decreases slightly using the robust version, while concentration rises slightly. However, the rank of Spanish provinces according to vulnerability is virtually identical to that of the original VTM index, as shown by the high correlation between the two score ranks (0.97). The same result holds if the indexes are weighted symmetrically, which suggests that the index is not sensitive to moderate changes in weighting. Notice, however, that although changing the definition of some variables almost does not change the relative value of the PCA weights, it slightly changes the classification of provinces, although the rank correlation with the VTM is, in any case, very large (0.80). Notice that changing the variables' definition alters weights and the factors themselves, which might change the distribution of individual factors across territories. Overall, the results of these two analyses suggest that the evidence offered by the VTM indicator is robust to the choices made in its construction.[3]

5. Discussion and implications

The analysis of market vulnerability based on a composite index constructed with 2019 data (before the Covid-19 pandemic) has made it possible to synthesize the relative position of Spanish provinces in terms of vulnerability in a single measure. We have found all kinds of tourism specialization patterns among the provinces with topmost (and least) vulnerable markets: sun and sand, urban, cultural and heritage, and rural. This implies that no single tourism specialization casuistry summarizes the destinations vulnerability associated with their source markets to a great extent. In fact, the derived PCA weights suggest all the factors behind the TMV index are relevant (proximity, seasonality, market concentration and economic profile). It is important to note that the results are robust to potentially subjective choices that could have been made in the construction of the index.

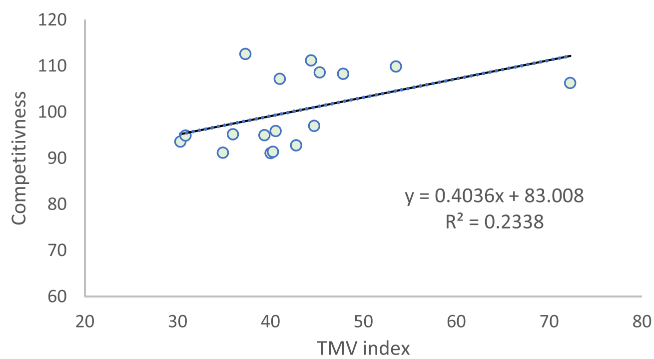
The Balearic Islands stand out among the most vulnerable provinces. Seasonality is very high in this province, with a predominant position of non-proximity international markets. The second place is occupied by the province of Barcelona, determined by the specific market structure of the Catalan capital, which is marked by the predominance of distant markets. In third place is the province of Granada, where the low domestic weight and the great volume of distant tourists, attracted by its monumental heritage, determine its vulnerability. Madrid appears in fourth place, with the effect of the state capital and the weight of its

[3] Ridderstaat and Nijkamp (2016) have carried out a methodological analysis in line with that of the present paper but for the small islands. In this sense, the comparative methodological analysis has some relevant differences. Thus, and although some dimensions included in their index (distance dimension and market concentration) have some similarities, this is not the case for intensity. In addition, in the present paper there is a greater detail of factors and a more complete analysis of the vector of weights. Regarding the latter aspect, and although the analysis focuses on the emerged weights of the PCA, the impact of the outliers and the results with homogeneous weights are analyzed in Ridderstaat and Nijkamp (2016) only homogeneous weighting were considered.



Notes: tourism intensity is defined as the total number of hotel travelers. Source. Own elaboration.

Fig. 5. Relationship between the TMV index and tourism intensity. Notes: tourism intensity is defined as the total number of hotel travelers.
Source. Own elaboration.



Notes: Results are for Spanish regions. The index of Competitiveness was obtained from Exceltur (2018).
Source. Own elaboration.

Fig. 6. Relationship between the TMV index and tourism competitiveness Notes: Results are for Spanish regions. The index of Competitiveness was obtained from Exceltur (2019).
Source. Own elaboration.

Table 5
Robustness analyses: implicit weights and Spearman rank correlation.

	DOM	NEAR	REM	CONC	SEAS	INC	Rank correlation with the VTM
RB1	14%	16%	18%	19%	14%	18%	**0.97**
RB2	17%	17%	17%	17%	17%	17%	**0.98**
RB3	22%	13%	21%	14%	17%	13%	**0.80**

Notes: RB1 uses weights obtained from a PCA version robust to outliers; RB2 uses symmetric weights for all individual factors; RB3 changes the definition of some of the variables used for individual factors and recomputes the PCA-based weights. The last column provides the Spearman rank correlation with the scores obtained by the original VTM index.
source: own elaboration.

distant international markets. However, note also that among the ten most vulnerable provinces are the Galician provinces of Lugo (rural) and La Coruña (Way of St James). In contrast, among the least vulnerable, we also find Mediterranean provinces offering the typical sun and sand product, such as Huelva (which is the least vulnerable of all provinces in terms of tourism), Castellón, or Murcia, explained by the relatively high predominance of the domestic market, which provide them with protection to exogenous demand shocks.

The analysis of the results has shown in the first place that the vulnerability of markets is associated with the magnitude of the demand. The provinces with the highest demand (which may also be the most competitive) are also the most vulnerable in terms of their demand markets. In this sense, in the future Spain needs to break down this association to combine demand growth with lesser vulnerability. Until now, Spanish destinations have been mostly concerned with expanding demand, believing that tourism could grow indefinitely (Williams, 2009; Pridaux et al., 2020). Therefore, destination managers and policymakers must include destinations risk and vulnerability reduction among their strategic objectives.

Secondly, we show that the TMV index is well correlated with the tourism results produced during the pandemic (summer of 2020 results). That is, even if the heterogeneity in terms of Covid-19 tourism resilience across destinations may be also explained by factors other than the market structure vulnerability, this component accounts for an important share of the variability. In this context, Duro, Pérez-Laborda, and Fernández-Fernández (2022) confirm that the weight of the domestic market in 2019 is crucial to explain the differentials in provincial tourism results obtained in the summer of 2020 in Spain.

Until now, competitiveness has presided the debates on the present and future of tourism destinations to a large extent (Mendola & Volo, 2017; WEF, 2019). However, we find that the most vulnerable territories (Spanish regions) are precisely those that are considered more competitive. In this context, it is necessary to revise the methodological approach to competitiveness by either adjust competitiveness to consider the underlying risks and vulnerabilities, or, directly, calculate risk and vulnerability indexes to be jointly analyzed with competitiveness by the destination management and policymaker (EIB, 2020; Salinas-Fernández et al., 2022). We feel that is an important and pressing issue in the current context.

Let us synthesize four important policy implications based on the different provincial results that we obtained: firstly, destinations must guarantee a sufficiently large volume of proximity markets in their source of incoming tourists, especially the domestic market and the nearby international market. This observation changes the strategic recommendations for destinations that have been issued until now, typically focused on attracting distant markets such as Asia, which usually have a larger economic impact, but that rise concerns in terms of vulnerability. Now, vulnerability concerns would advocate to retain as much demand as possible from as near as possible (i.e., the domestic, nearby or EU demands, by this order) as a security cushion, consistent with the results in Gössling et al. (2020) or Navarro-Jurado et al. (2020). Secondly, seasonality appears as a factor that increases the vulnerability of tourism markets, as the yearly results depend crucially on what may happen in specific months and seasons of the year, which may be disrupted by exogenous shocks. These considerations add a new dimension to the impact and study of the destinations' high seasonality, which should further incorporate the vulnerability aspect that it generates. Thus, the reduction of seasonality would not only be good in terms of social, economic, and environmental sustainability, as noted in Duro (2016), for example, but also in terms of risk and vulnerability (Batista e Silva et al., 2018; Duro et al., 2021). In the third place, destinations must diversify their source markets, in line with the concept of portfolio diversification used to hedge financial risk (Gallego & Font, 2019). Notice that the strategy of reducing concentration is independent of the market and is complementary to the objective of reducing the distance of the source markets. Finally, improving demand profiles in favor of higher income markets is good in terms of impact and vulnerability reduction.

Therefore, our results suggest that, in Spain (possibly in other parts of the world as well), some of the most competitive and large destinations in terms of demand are also the most vulnerable destinations. Given the objective of this paper, this might not be the most suitable place to analyze in detail the reasons behind those findings. Nonetheless, some of the reasons are probably the lack of diversify and the constant focus on easy/lucrative mass markets by tourist operators and stakeholders, which are risk averse and have short-term strategic objectives. In addition, the large growth patterns observed in the tourism sector revenues in Spain has favored and protected this myopic behavior. In this context, the mitigation of seasonality and the attraction of more diversified tourist profiles, may require large (and different) investments, which may contradict this preference for short-term objectives and risk aversion. Altogether, vulnerability requires an integrated joint effort by private and public institutions and governments in terms of investment and policy, and a definitive and continued strategic change, which should focus on putting long-term objectives in first place.

6. Concluding remarks

The Covid-19 pandemic has disrupted the foundations on which countries and destinations tourism strategies were built, mainly based on continuous growth and expansion of the tourism activity to attract tourists from new markets and large developing countries. The pandemic shock has reminded us that tourism is exposed to multiple risks, like other economic sectors. Therefore, tourism stakeholders must consider managing risk as a basic objective in their strategic portfolio. In this context, it is important to generate knowledge that allows the detection of risks, evaluate policies, and make advanced planning possible. In this sense, this paper focuses on vulnerability indicators associated with the destination's source market structure.

Thus, six indicators associated with the structure and composition of the incoming tourism source markets have been identified, which are consistent with the multidimensional nature of vulnerability. These indicators are strongly linked to market vulnerability, are easily accessible and interpretable, and are associated with dimensions such as distance (the more distant the source markets, the more vulnerable the destination), seasonality and market concentration (are also positively associated with vulnerability), and the income profile (which is assumed to correlate negatively). To deal with this multiplicity of indicators, we synthesize these factors into a composite index using PCA to derive weights (along with various robustness analyses to the weights). This index provides a tool for facilitating the interpretation process and an analytical framework for evaluating the results of policies and therefore increase the resilience of tourism destinations.

The framework proposed in this paper has been empirically implemented for the Spanish provinces, as Spain is one of the most important countries in terms of international attraction of tourists and has good territorial data. The composite index has allowed us to rank the provinces according to the vulnerability of their market structure. The interplay of different factors has led us to find all kinds of specialization patterns among the most vulnerable provinces, from provinces primarily offering the classic sun and sand product (such as the Balearic Islands), to provinces with large capital cities (such as the State capital, Madrid), or even to provinces with large cultural and interior tourism (Granada or Lugo). The index correlates well with the Covid-19 pandemic 2020 summer results in terms of tourism activity, explaining a significant portion of the variability in resilience across territories. Perhaps another interesting aspect is that market vulnerability seems to be positively associated with the volume of tourism demand: the provinces that generate more touristic activity are more vulnerable. The result implies that decision-makers must conduct policies to decouple these two variables. It seems crystal clear that vulnerability and competitiveness have little to do with each other, at least in the short term. The analysis for the Spanish provinces suggests a strong positive relationship between these two variables: the most competitive provinces are also the most vulnerable. This result places serious concerns on the current definition of competitiveness, which may require reformulation to better include risk and vulnerability. These are important aspects that are not being properly captured by this indicator.

Our results indicate that reducing vulnerability must be considered as a primary objective by the destinations managers and policymakers. This objective must remain even after the Covid-19 has passed because vulnerability issues go well behind the pandemic. Therefore, maintaining a solid and strong enough domestic and nearby international incoming flow of tourists, reducing seasonality and market concentration in terms of the demand sources, together with attracting higher-income visitors, must be key objectives in the medium- and long-run tourism strategies and policies. However, this paper considers only the vulnerability associated with the source market structure. More generally speaking, the list of factors linked with vulnerability may be considerably larger (e.g., climate change, tourism dependence, etc.). However, in our view, the final effect of external shocks on tourism activity are highly conditioned by the type of vulnerability analyzed in this work.

In this context, vulnerability must be properly managed in order for the necessary transformation of the tourism sector to occur (Mckinsey & Company, 2020). Moreover, decision-makers must be equipped with tools that can allow them to monitor vulnerability, such as the composite index proposed in this paper. This tool may help destination managers and policymakers to assess and design new and different strategies, not only in terms of profitability, but also in terms of risk and vulnerability reduction in the tourism sector.

Credit author statement

J.A. Duro and A. Pérez-Laborda 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. M. Fernández and Antonio Osório have contributed to the conceptualization and writing of the paper.

Data availability

Data will be made available on request.

Appendix

Table A1
Indicators of market vulnerability and VTM across Spanish provinces.

Province	DOM	NEAR	REM	CONC	SEAS	INC	VTM
Baleares	1	0.98	0.06	0.65	1	0.47	**66.6**
Barcelona	0.86	0.84	0.77	0.09	0.17	0.37	**56.1**
Granada	0.51	0.85	0.93	0.28	0.07	0.44	**54.7**
Madrid	0.52	0.87	1	0.22	0.04	0.38	**54.5**
Toledo	0.31	0.79	0.98	0.32	0.11	0.56	**53.8**
Alicante	0.46	0.95	0.18	1	0.26	0.56	**53.4**
Lugo	0.24	0.78	0.6	0.04	0.57	0.86	**52.0**
Málaga	0.69	0.92	0.31	0.21	0.33	0.37	**48.0**
Coruña, A	0.33	0.69	0.59	0.05	0.44	0.69	**47.9**
Valencia	0.48	0.87	0.61	0.09	0.15	0.51	**47.7**
Sevilla	0.6	0.71	0.76	0.17	0.08	0.29	**47.3**
Zaragoza	0.26	0.58	0.76	0.39	0.14	0.57	**46.6**
Girona	0.63	0.10	0.21	0.65	0.61	0.63	**46.4**
Córdoba	0.42	0.7	0.73	0.16	0.14	0.46	**46.0**
Tarragona	0.46	0.32	0.29	0.61	0.83	0.38	**45.9**
Segovia	0.17	0.73	0.8	0.14	0.23	0.57	**45.5**
Gipuzkoa	0.49	0.37	0.54	0.22	0.22	0.73	**45.5**
Cantabria	0.18	0.66	0.51	0.12	0.57	0.69	**45.3**
Badajoz	0.19	0.34	0.78	0.67	0.2	0.52	**45.1**
Cádiz	0.36	0.83	0.4	0.19	0.46	0.42	**44.0**
León	0.2	0.67	0.57	0.01	0.39	0.72	**43.8**
Asturias	0.14	0.58	0.59	0.07	0.53	0.66	**43.3**
Las Palmas	0.91	0.98	0	0.59	0.01	0.11	**43.2**
Teruel	0.07	0.52	0.48	0.24	0.25	1	**42.8**
Rioja	0.18	0.61	0.56	0.08	0.28	0.78	**42.7**
Albacete	0.03	0.71	0.67	0	0.15	0.86	**42.0**
Cuenca	0.07	0.74	0.62	0.09	0.21	0.74	**41.9**
Tenerife	0.82	1	0.05	0.7	0	0	**41.8**
C. Real	0.09	0.59	0.68	0.24	0.16	0.66	**41.3**
Bizkaia	0.43	0.65	0.47	0.03	0.19	0.49	**39.9**
Pontevedra	0.23	0.14	0.36	0.43	0.55	0.7	**39.5**
Navarra	0.24	0.37	0.42	0.2	0.33	0.75	**39.3**
Ávila	0.07	0.59	0.61	0.06	0.27	0.67	**38.9**
Palencia	0.22	0.18	0.35	0.17	0.36	0.94	**37.8**
Huesca	0.13	0.09	0.32	0.59	0.41	0.79	**37.4**
Salamanca	0.29	0.36	0.65	0.2	0.27	0.35	**37.3**
Jaén	0.08	0.64	0.56	0.1	0.17	0.61	**37.0**
Burgos	0.35	0.29	0.31	0.15	0.39	0.67	**36.8**
Soria	0	0.45	0.44	0.02	0.28	0.91	**35.5**
Lleida	0.14	0	0.3	0.59	0.26	0.85	**35.0**
Almería	0.2	0.84	0.24	0.17	0.7	0.09	**34.7**
Murcia	0.19	0.77	0.4	0.11	0.18	0.4	**34.4**
Araba	0.27	0.36	0.4	0.09	0.22	0.58	**33.6**
Cáceres	0.12	0.39	0.53	0.18	0.25	0.48	**33.2**
Guadalajara	0.07	0.52	0.54	0.03	0.14	0.6	**33.1**
Ourense	0.06	0.09	0.45	0.43	0.23	0.67	**32.0**
Zamora	0.05	0.24	0.39	0.14	0.35	0.73	**31.9**
Castellón	0.12	0.36	0.39	0.17	0.49	0.3	**29.9**
Valladolid	0.13	0.1	0.36	0.27	0.1	0.46	**24.4**
Huelva	0.2	0.07	0.09	0.38	0.68	0.12	**23.4**

Source: Own elaboration.

Table A2
Indicators of market vulnerability and VTM across Spanish regions.

Region (CCAA)	DOM	NEAR	REM	CONC	SEAS	INC	VTM
Balears	1.00	0.98	0.04	1.00	1.00	0.56	72.3
Madrid	0.45	0.82	1.00	0.25	0.03	0.44	53.5
Cataluña	0.68	0.46	0.61	0.02	0.34	0.53	47.8
C. Valenciana	0.33	0.84	0.36	0.35	0.25	0.62	45.3
Castilla- la Mancha	0.02	0.59	0.84	0.15	0.13	0.83	44.7
Canarias	0.85	1.00	0.00	0.93	0.00	0.00	44.4
Cantabria	0.05	0.47	0.50	0.11	0.57	0.88	42.8
Andalucía	0.42	0.72	0.53	0.00	0.26	0.40	41.0
Galicia	0.15	0.24	0.50	0.10	0.47	0.91	40.6
Rioja, La	0.06	0.39	0.55	0.06	0.27	1.00	40.3
Aragón	0.06	0.16	0.63	0.40	0.20	0.89	40.0
Asturias	0.00	0.36	0.59	0.02	0.53	0.84	39.4
País Vasco	0.34	0.24	0.48	0.08	0.20	0.74	37.3
Navarra	0.12	0.02	0.41	0.28	0.33	0.95	36.0
Extremadura	0.02	0.00	0.67	0.56	0.22	0.61	34.9
Murcia	0.06	0.65	0.39	0.10	0.17	0.46	30.9
Castilla y León	0.08	0.05	0.49	0.09	0.28	0.73	30.3

Source: Own elaboration.

Fig. A.1. Distribution of the VTM index across Spanish regions.
Source: Own elaboration.

Table A3
Detailed province scores in robustness analyses.

RB1		RB2		RB3	
Balears	66.21	Balears	69.33	Balears	69.32
Alicante	58.56	Alicante	56.99	Barcelona	58.66
Toledo	53.11	Barcelona	51.48	Alicante	51.47
Granada	52.31	Granada	51.39	Tarragona	51.07
Lugo	51.43	Lugo	51.37	Girona	50.24
Madrid	51.37	Toledo	51.30	Granada	48.33
Barcelona	50.32	Madrid	50.57	Málaga	48.06
Badajoz	47.30	Tarragona	48.19	Madrid	46.96
Tarragona	47.26	Málaga	47.13	Sevilla	43.61
Zaragoza	46.84	Girona	47.12	Valencia	43.49
Girona	46.81	Coruña, A	46.49	Cádiz	43.39
Coruña, A	46.38	Cantabria	45.50	Las Palmas de G.C.	43.30
Málaga	45.71	Valencia	45.23	Pontevedra	42.92
Cantabria	45.57	Zaragoza	45.05	Gipuzkoa	42.78
Valencia	45.20	Badajoz	44.73	S.C de Tenerife	42.30
Segovia	45.01	Cádiz	44.31	Coruña, A	41.56
Teruel	44.62	Segovia	43.83	Toledo	41.37
Córdoba	43.86	Sevilla	43.70	Lugo	41.31
Cádiz	43.65	Las Palmas de G.C.	43.40	Cantabria	40.91
Sevilla	43.56	Córdoba	43.37	Huesca	40.44
Gipuzkoa	43.41	Gipuzkoa	42.89	Lleida	40.08
Asturias	43.12	Asturias	42.89	Córdoba	38.95
León	42.94	S.C de Tenerife	42.83	Badajoz	38.80
Cuenca	42.41	León	42.61	Zaragoza	37.50
La Rioja	42.36	Teruel	42.54	Asturias	37.15
Las Palma de GC.	42.22	La Rioja	41.41	Palencia	36.42
Albacete	42.19	Cuenca	40.97	Bizkaia	35.89
Ciudad Real	42.18	Albacete	40.42	Navarra	35.71
S.C de Tenerife	42.09	Pontevedra	40.29	Teruel	35.43
Pontevedra	41.01	Ciudad Real	40.26	León	35.27
Huesca	40.80	Huesca	38.88	Almería	35.09
Navarra	39.27	Navarra	38.51	La Rioja	34.33
Ávila	38.95	Ávila	37.84	Burgos	33.97
Lleida	38.11	Bizkaia	37.70	Segovia	33.95
Palencia	37.86	Almería	37.35	Castellón	33.39
Bizkaia	37.41	Palencia	36.89	Huelva	33.06
Jaén	37.30	Jaén	36.02	Salamanca	32.37
Soria	36.31	Burgos	35.88	Ourense	32.13
Salamanca	35.86	Lleida	35.74	Álava	31.23
Burgos	35.81	Salamanca	35.45	Ciudad Real	30.79
Almería	35.65	Soria	34.88	Zamora	30.53
Murcia	34.40	Murcia	34.08	Albacete	30.42
Ourense	34.19	Cáceres	32.48	Murcia	30.22
Cáceres	33.44	Ourense	32.04	Cuenca	29.97
Guadalajara	32.90	Álava	32.04	Soria	29.87
Zamora	32.73	Guadalajara	31.72	Ávila	29.66
Álava	32.41	Zamora	31.66	Cáceres	28.47
Castellón	30.30	Castellón	30.50	Jaén	28.26
Valladolid	24.99	Huelva	25.87	Guadalajara	25.53
Huelva	24.80	Valladolid	23.67	Valladolid	25.21

Source: Own elaboration.

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