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A Spatial Origin-Destination Analysis of International Tourism Demand. The Case of Italian Provinces

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To my father, keeping an eye on me from somewhere in the sky. You are always in my heart.

"Space and time are not realities in the phenomenal world, but the modes under which we perceive things apart. They are not infinitely large nor infinitely divisible, but are essentially limited by the contents of our perception"

Karl Pearson

"everything is related to everything else, but near things are more related than distant things"

W. Tobler

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Declarations

The present thesis is the result of study and research carried out during these years in the Department of Economics, Business and Statistics at the University of Palermo, and during my visiting period in the Department of Economics, Econometrics and Finance at the University of Groningen. The first chapter is sole-authored. Chapter 2 is written in co-authorship with Prof. Maria Francesca Cracolici and Prof. Davide Piacentino, and it has been published as Costantino et al. (2020). Chapter 3 has been written in co-authorship with Prof. Maria Francesca Cracolici and Prof. J. Paul Elhorst. Chapter 4 is co-authored with Prof. Maria Francesca Cracolici and Prof. J. Paul Elhorst. For the development and writing of the entire work, I benefited the helpful suggestions and comments from my supervisors.

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Introduction

In recent decades, tourism and leisure activities have experienced remarkable growth, as more and more people use their spare time for these activities. The increasing ease and speed of travel worldwide have significantly contributed to the prosperity of the tourism sector, which has become one of the crucial sectors for the economic prosperity of many regions in the world. The increasing importance of tourism boosts the need for destination managers to have accurate information on the determinants and forecasts of demand. Consequently, the study of tourist flows has attracted increasing attention from both academics and practitioners.[1]

As will be discussed in Chapter 1, although tourism is a local activity, and reasonably would include an element of spatial dependence, the literature on this subject has paid little attention to the spatial analysis of tourism demand (among others, see Deng and Athanasopoulos, 2011; Yang and Wong, 2012; Marrocu and Paci, 2013; Yang and Fik, 2014; Pompili et al., 2019). This thesis aims to enrich this new stream of literature both methodologically and empirically. Its aim is to explore Italian tourism demand in order to assess the competitive ability of Italian tourist destinations, while taking into account the spatial features of tourism and information on both the origin and the destination of tourists.

To achieve this, firstly we explore the competitiveness of Italian destinations and the presence of spatial spillover effects by means of the decomposition method of spatial shift-share by proposing a new decomposition formula, and using it to decompose spatial flows of tourists with both origin and destination information. The novelty of the proposed spatially extended shift-share formulation is that gives us the possibility, within a single formula, of assessing 'net' spatial competitive and allocation effects at both destination and neighbourhood level. The spatial competitive effects obtained from this proposal can be considered as 'net' because they take account of the influence of industrial specialization.

Secondly, in the context of the Great recession, we explore the ability of Italian destinations to resist and recover from crisis shock, taking into account the spatial features of the phenomenon and both destination and origin characteristics. In doing so, we used

[1] See, Song and Li (2008) for a detailed review on tourism demand.

a Dynamic Spatial Panel Data (DSPD) model with common factors within the Origin-Destination (O-D) framework, which is still a new practice in tourism research. Finally, we explore if and how differences in destination resilience depend on industry structure and the tourist vocation of Italian destinations.

The statistical analyses in Chapter 2 and Chapter 4 have been performed by using the statistical software R. The estimations of the statistical models presented in Chapter 3 have been carried out by means of Matlab routines, whereas the explanatory analysis and the graphs of results have been made using R.
The thesis has been structured as follows:

- **Chapter 1.** provides an overview of the main studies using a spatial approach in the analysis of tourism demand. The first part of the chapter, beginning with previous reviews on the topic (see, among others Song et al., 2019, 2012), provides a brief excursus on the main models used in the analysis of tourism demand, highlighting the fact that little attention has been paid to the spatial dimension of the phenomenon. The second part of the chapter focuses on the spatial models and methods applied in tourism research. In this regard, we firstly discuss the main modelling approaches employed in analyzing tourism demand, and distinguish between those falling into the destination-only setting (i.e. considering only information on the destination) from those using an Origin-Destination (O-D) theoretical framework. The theoretical and empirical strategy followed throughout the thesis fits into this latter stream of literature. Secondly, we discuss the developments of the decomposition approach of shift-share with particular attention to spatial developments. This overview of the literature enables us to identify the main gaps and to highlight the contribution of the thesis both methodologically and empirically.

- **Chapter 2.** This chapter is a methodological and empirical contribution which explores the competitiveness of Italian tourist destinations (NUTS3 regions) and assesses the presence of spatial spillover effects, taking into account both destination and origin. In the first part, we briefly discuss the main shift-share formulations to be found in the literature with particular attention to spatial developments, and then discuss the proposed spatial shift-share formulation, highlighting the novelty of its use. In the second part, an empirical application to inbound tourism demand in the 110 Italian provinces (NUTS3 regions) is presented. We use data collected by the Italian Institute of Statistics (ISTAT), from 2011 to 2014, on nights spent by non-residents in Italian provinces by country of origin. To the best of our knowledge, this is the first attempt to apply spatial shift-share analysis to disentangle the contribution to growth of tourist competitiveness and specialization at regional level from that of the neighbourhood. This application is interesting from the spatial perspective, not only because spatial spillover effects can be explored, but also because shift-share analysis is applied to decompose spatial flows accounting for information on both destination and origin. The analysis reveals virtuous scenarios in Sardinia and other destinations in the South of the country, as well as the regional advantage of well-known destinations in the North-East and in the Centre-North of Italy. Furthermore, the analysis also enables the best and worst-performing destinations to be identified.

- **Chapter 3.** In this chapter, we investigate the presence of spatial and temporal dependence in Italian inbound tourism demand, and explore its main determinants. In doing so, we carry out an econometric analysis based on the recently proposed Dynamic Spatial Panel Data model with common factors (DSPD-WCF) (for recent applications, see Halleck Vega and Elhorst, 2016; Ciccarelli and Elhorst, 2018; Elhorst et al., 2020), which is applied within the Origin-Destination (O-D) framework. The model specification used in this chapter enables us to simultaneously account for spatial, temporal, and spatiotemporal features of tourist flows, along with the presence of cross-sectional dependence and both origin and destination characteristics. The empirical analysis proposed in this chapter is based on unilateral tourist flows in the 110 Italian provinces from 23 countries of origin, for the period 2004-2017. Data used in this study are collected by the Italian Institute of Statistics (ISTAT), and freely available. There are some novel aspects of this analysis that are worthy of note. One is, that it is the first effort to apply a DSPD-WCF within the Origin-destination framework to analyze Italian inbound tourism demand. Another novelty is that, the model specification enables us to obtain spatial spillovers which are straightforward to interpret. Finally, we are able to assess tourist attractiveness at regional level accounting simultaneously for both origin and destination characteristics, along with the presence of weak and strong cross-sectional dependence. The empirical findings give us greater understanding of spatial and temporal dependence in inbound tourist flows, as well as of the presence of spatial spillover effects of some explanatory variables. The empirical evidence emerging from this study highlights the need for cooperation among destinations, which is important because an integrated and coordinated plan for tourism may improve the attractiveness of Italian destinations.

- **Chapter 4.** Here we provide an empirical analysis to evaluate the resilience of Italian destinations to the Great recession shock and to explore the main determinants of destination resilience. To do this, we adapted the theoretical framework used by Doran and Fingleton (2018) to tourism. The chapter proposes a measure of tourism resilience in terms of resistance and recovery. The former is the ability of a destination to absorb the economic shock, whereas the latter is the ability of such a destination to react to the adverse shock. These two quantities have been measured by comparing actual tourist flows with counterfactual ones. Counterfactual series represent the expected level of tourist flows in the absence of the crisis shock, and they are generated based on the estimates of the model defined in Chapter 3. The second step of the analysis consists of a regression analysis to explore if and how industrial structure and tourism vocation affect destination resilience. By looking at resistance and recovery jointly, the analysis enables us to cluster destinations as resilient and not resilient. We find a varied group of 13 well-known cultural and coastal destinations that can be seen as 'best' in terms of resilience. The regression analysis highlights the fact that a local concentration of tourism activities and specialization have a positive effect on resistance and a negative effect on recoverability. In addition, the vocation of tourist destinations aids resistance to the crisis, but may have negative effects on their ability to recover.

Finally, some concluding remarks, summarising the main empirical findings of the thesis, have been reported. This thesis lends support to the idea that the spatial dimension is a key factor that needs to be accounted for in the analysis of tourism, and that the complexity of the spatial dependence structure of tourism should be seen as an opportunity, rather than a limitation. Neglecting the spatial dimension may lead to serious estimation and inference issues, mainly related to misleading inference, inefficient estimates, and biased tests. Furthermore, taking into account the spatial dimension brings important advantages from the empirical viewpoint. For example, spatial analyses enable policy makers to understand the complex relationships between regions, as well as the presence of spatial spillover effects, giving them a detailed picture of the phenomenon. This is crucial information for policy makers, because it enables them to plan policy strategies with potential spatial spillover effects in mind. Finally, taking into account the spatial dimension enables us to have information on and account for the spatial heterogeneity of destinations.

Chapter 1

An overview of the literature on spatial analysis of tourism demand

1.1 Introduction

The notable increase in demand for tourism throughout the world over recent decades has made the tourism industry one of the key sectors for economic growth in many parts of the world. The increasing importance of the leisure sector has meant that Destination Management Organizations (DMOs) need to have reliable information on the determinants and forecasts of demand and their policy implications. As a consequence, tourism demand modelling and forecasting are subjects of research that have attracted a great deal of interest from both academics and practitioners (Song and Li, 2008).

According to the recent review by Song et al. (2019), more than 600 studies on the subject have been published over in recent decades, most of these focusing on international tourism demand.

Song et al. (2019) classified the methodological approaches to the analysis of tourism demand into four categories, namely Time Series models, Econometric models, Artificial Intelligence (AI) based models, and Judgemental Methods. The first three are quantitative approaches, whereas the latter has been used in both quantitative and qualitative analyses. As far as time series models are concerned, Song et al. (2019) divide them into two sub-categories basic and advanced. Among the basic time series models, the authors, include AutoRegressive (AR) models, Single Exponential Smoothing, Moving Average (MA), and Historical Average. They find these models used frequently in the literature, mainly due to both their ease of application and their ability to model historical data.

Advanced time series models include advanced exponential smoothing, different types of trend analysis, and Box-Jenkins methods (e.g. ARIMA models). Various ARIMA models can be found in the literature on tourism demand, accounting for more than 60% of studies employing time series models (Song et al., 2019). The seasonal nature of tourism led to the need for accounting for seasonality in the analysis of tourism demand and Song et al. (2019) found that seasonality is accounted for in many of the papers in their review, its importance being reflected in the increasing use of seasonal ARIMA (SARIMA) and some basic time series models which account for seasonality (termed seasonality-sensitive by the authors). Song et al. (2019) also noted some recent developments based on ARIMA models applied in tourism research, like the ARFIMA, the ARIMA-GARCH, and the SARIMA-In models.

As far as econometric models are concerned, the increasing interest in these models animated the debate on the causal relationship between tourism demand and its main determinants. Single static regression is the simplest econometric model, which was employed in earlier studies to analyse tourism demand, and more recently has been used as a benchmark model. The need to resolve problems associated with this basic model and to account for the complex features of tourism demand led to the application of more sophisticated econometric models. Of these, the Distributed Lag model (DL), the Autoregressive Distributed Lag Model (ADLM), and the Error Correction Model (ECM) have been applied to tourism research to account for inter-temporal dependence in tourist flows. As noted by Song et al. (2019), both the ADLM and the ECM play an important role in the analysis of tourism demand, and half of the studies in their review employing econometric models used the ADLM and the ECM models. In order to account for inter-temporal dependence in multiple time series, the Vector AutoRegressive model (VAR) and the Vector Error Correction Model (VECM) have been applied to the tourism field. In their comprehensive review, Song et al. (2019) identified 27 papers employing these models.

Additionally, among the econometric models, panel data regression can also be used to analyze tourism demand, but as noted by Song et al. (2019) their use in tourism is still relatively rare. In the econometric approach, an important issue is the selection of the variables to use in the model. There are two main approaches to their selection, the specific to general, and the general to specific. The former starts with the estimation of the simplest model specification and then proceeds with the testing of additional explanatory variables. The latter starts with the estimation of the most general model specification and then, step by step, nonsignificant variables are deleted from the model until the specification is satisfactory. Song et al. (2019) found the specific to general approach has been the traditional choice in tourism demand forecasting with the general to specific approach being a relative newcomer.

The third category identified by Song et al. (2019) is Artificial Intelligence (AI) models. These are data-driven techniques with good forecasting ability in the case of complex data structure for which relationships among data are unknown. AI-based techniques have been criticised for their lack of theoretical foundation and explanatory ability. Nevertheless, they are widely used to forecast tourism demand. Among the most commonly used are the Support Vector Regression (SVR), the fuzzy time series, the rough sets approach, the grey theory, and Artificial Neural Networks (ANNs). Of these, the latter is the most widely used in tourism research, with different models being proposed over the years including, the MultiLayer Perception (MLP), the Radial Basis Function (RBF), and the Elman network.

The fourth category of approaches to the analysis of tourism demand is the judgemental method. Song et al. (2019) found that, in the field of tourism, the two most widely applied techniques are Delphi methods and scenario building. The Delphi method has recently been employed to address new research questions such as rural tourism planning, to find indicators for sustainable tourism, and to measure the impact of economic crises on tourism demand. Song et al. (2019) also point out that some empirical studies revise quantitative forecasts with the Delphi method while some others combine time series and forecasts from econometric models with Delphi surveys and scenario analysis to improve the accuracy of their results.

Song and Li (2008) stated that "*There has not been a panacea for tourism demand forecasting*" (p. 203) and indeed Song et al. (2019) found 24 studies that use combined and hybrid models to improve forecasting results. They noted that most of these studies have been published since the late 2000s, and the majority of them show that combined and hybrid models perform better than other models. They expect that in the future combined and hybrid models will attract more attention in tourism research. In their 2019 work Song et al. also traced the historical development of forecasting methods. During the 1960s and 1970s, the simple regression method was primarily used and the focus was on determinants of tourism demand. During the 1980s, researchers started to consider the time series perspective of tourist flows, and in the 1990s the application of advanced time series models increased. During the 2000s, econometric models, artificial intelligence based models, and combined and hybrid methods became very popular. Since the 2010s, the advanced time series and econometric models have been the most widely used in tourism demand forecasting.

Although the study by Song et al. (2019) is a well-structured and exhaustive review, it, as in the previous study by Song et al. (2012), neglects the flourishing literature focusing on the spatial dimension of tourism demand. In addition, Deng and Athanasopoulos (2011) noted that the two important and comprehensive reviews on the analysis of tourism demand by Li et al. (2005), and Song and Li (2008) also do not mention empirical studies using spatial methods and models to analyse tourism demand.

That appears paradoxical since tourism is a local activity, and hence, tourism flows in one territory are likely to be strongly dependent on its amenities and on tourism demand in neighbouring destinations. For instance, tourists tend to visit multiple neighbouring destinations to maximise their experience and to reduce travel costs and distance. Con-

sequently, it is reasonable to think that the spatial dimension could play an important role in the analysis of tourism flows, and therefore, that the attractiveness of one destination can benefit from spatial spillover effects (see among others, Yang and Wong, 2012).
Recently, in the light of these considerations, spatial econometrics literature has received increasing attention in regional studies. The increasing popularity of spatial econometrics has led to a growing interest in the application of spatial models in tourism research. Indeed, recent studies employing spatial models, have confirmed the presence of spatial spillover effects in tourism and the importance of taking into account the spatial dimension in tourism demand modelling and forecasting (see among others Deng and Athanasopoulos, 2011; Marrocu and Paci, 2013; Yang and Fik, 2014; Yang and Zhang, 2019; Xu et al., 2020).
Furthermore, spatial econometric models are helpful to policy makers in drawing up tourism policies at both the national and local level. Modelling spatial effects enables the presence of spatial spillovers to be investigated, which in the case of tourism demand, means exploring if and how a destination could benefit from the presence of highly attractive destinations in the neighbourhood. This information enables policy makers to plan a more efficient regional strategy. For example, in the presence of positive spatial spillovers among destinations in a given area, policy makers might decide in favour of a cooperation strategy to improve the attractiveness of the entire region.

In the light of the above considerations, the aim of this chapter is to provide a structured overview of the main studies that use a spatial approach to the analysis of tourism demand.

Beginning with previous reviews on the topic (see among others Song et al., 2019, 2012), the chapter aims to integrate the existing literature by offering a focus on the main approaches to the analysis of tourism demand from a spatial perspective. Firstly, the chapter introduces the main spatial modelling approaches used, and then focuses on the decomposition approach (i.e. the Shift-Share Analysis, SSA) drawing attention to its development in a spatial perspective. We focus also on studies using the decomposition method of shift-share since it enables us to analyse tourist flows according to an Origin-Destination (O-D) perspective.

This analysis has been carried out so as to identify the main gaps in the literature in order to highlight the methodological and empirical contribution of this thesis.

The rest of the chapter is structured as follows. Section 2 presents the sample of the analysed studies. In Section 3, we introduce and describe the main spatial models used in the literature to analyse tourism demand and examine the main developments of the spatial method of shift-share.

1.2 Sampling the literature

To identify the key studies on tourism demand a detailed search of various databases has been carried out, including Scopus, Google Scholar, as well as citations from published studies. Different key words have been used to select papers employing spatial models in tourism demand modelling and forecasting such as Spatial models for tourism demand, Tourism demand spatial modelling, Spatial effects in tourism demand, Spatial spillovers in tourism, and Spatial models of tourism flows. After the exclusion of all the review papers, no-tourism, and no spatial analysis, we found 24 articles which explicitly consider spatial effects in the analysis of tourism.
In Table 1.1 a summary of the main characteristics of the studies has been reported; viz. scope of the analysis, applied model, explanatory variables, etc.
As far as shift-share analysis is concerned, the following key words have been considered: ‘Spatial shift-share in tourism’, ‘Spatial shift-share analysis and tourism demand’, ‘tourism competitiveness and spatial shift-share’. Our search yielded eight papers using spatial shift-share analysis of tourism.
Table 1.2 sketches out the main features of these articles. A more detailed description of the models and the SSA method applied to the analysis of tourism demand is reported in Section 3.

Table 1.1: Summary of spatial models

Article	Time	Research scope	Geo	Territory	Data	Method	W matrix	Y	Tour. flows	Explanatory variables	Spat. eff.
Zhang (2009)	1989-2005	Analyse determinants of international inbound tourism	China	31 provinces in mainland China	Panel	Spatial error panel	contiguity matrix and inter-region tourist flow	Annual tourist receipts	International	GDP, international trade value, tourism resources index, service and facility evaluation, dummy international airport, number of tourist agent, price of accommodation evaluation, proportion of nature reserved areas	We
Yang and Wong (2012)	2002-2009	investigate and estimate the spillover effects in inbound and domestic tourism flows	China	341 cities in mainland China	Panel	Spatial lag panel	k-nearest neighbours ($k = 5$)	tourist arrivals	domestic and international	# of star rated hotels, FDI relative to GDP, density of roads, total flights number at cities' airports, GDP, # of fixed-line and mobile phone subscribers to population, # national parks, # World Heritage Sites, # AAAA scenic spots, dummy for SARS	WY
Yang and Fik (2014)	2002-2010	spatial spill-over and spatial heterogeneity effects in regional tourism growth	China	342 prefectural-level cities in Mainland China	Panel	Spatial Durbin model and Geographically Weighted SDM	k-nearest neighbours	Log growth rate of total revenue	domestic and international	Total revenue of tourism in the first year of analysis, population density in 2002, GDP of tertiary economies to overall GDP, resource endowment index (weighted sum of World Heritage Sites, national parks, AAAA scenic spots), # star-rated hotels per capita, GDP growth rate	WY WX

(Continued on next page)

Table 1.1 *(continued)*

Article	Time	Research scope	Geo	Territory	Data	Method	W matrix	Y	Tour. flows	Explanatory variables	Spat. eff.
Romão and Nijkamp (2018)	2004-2011	competitiveness of European tourist destinations	Europe	237 European NUTS2 regions	Panel	spatial panel SARAR/ SAC	Rook-contiguity matrix	Gross Value Added in tourism	International	Log of nights spent, log of investment in tourism, importance of tourism in reg. GVA and employment (%). Among immaterial factors: work force with tertiary education, investment in research and development as share of reg. GDP (ID). Productivity in millions per worker.	WY We
Yang and Zhang (2019)	1987-2016	Spatial-temporal forecasting of inbound tourism demand in China	China	29 provincial cities	Panel	dynamic SAR and STARMA	3 different matrices: contiguity matrix, distance ($1/d^2$), flow-based matrix	Annual inbound tourist arrivals	International	Time lag of the dependent variable	WY WYt-1
Dong et al. (2019)	2004-2013	To analyse the impact of Air Pollution on Domestic Tourism	China	337 Chinese cities	Panel	SDM panel	inv. distance matrix, distance matrix with 800 km threshold (for robustness check)	log of tourist arrivals	domestic	Variable of interest: PM2.5 Control variables: Scenic (index of resource endowment, as number of 4A and 5A scenic spots), Hotel (# of star-rated hotels divided by local population), Transport (indicator of transportation infrastructures), GovSize (government size, measured as ratio of fiscal spending to local GDP), log of local GDP per capita, log of population	WY WX

(Continued on next page)

Table 1.1 *(continued)*

Article	Time	Research scope	Geo	Territory	Data	Method	W matrix	Y	Tour. flows	Explanatory variables	Spat. eff.
Deng and Hu (2019)	2006-2015	Investigate determinants and spill-over effects of outbound tourist flows in China	Silk Road countries	55 countries in the Silk Road initiative	Panel	spatial autoregressive panel model SAR	contiguity matrix and cultural distance matrix	number of Chinese tourists	outbound	Geographic Distance, Cultural Distance, Bilateral trade, tourism investment of China, level of tourism specialization (percentage of total tourism revenue to GDP), scale of inbound tourism market, level of development (GDP per capita in destination country), Information infrastructure (# of internet users/100), Transportation infrastructure (# departure flights from host country), political stability, civil rights	WY
Romão and Saito (2017)	2010	Spatial effects and determinants of tourism performance	Japan	46 prefectures	Cross-section	SARAR/ SAC	k-nearest neighbours ($k = 5$), and distance-based matrix (threshold dist. = at least one neighbour)	GDP per capita in tourism	domestic and international	Level of education, share of tourist regional GDP, regional employment, nights spent per capita, share of foreign nights spent, and length of stay.	WY We

(Continued on next page)

Table 1.1 *(continued)*

Article	Time	Research scope	Geo	Territory	Data	Method	W matrix	Y	Tour. flows	Explanatory variables	Spat. eff.
Bo et al. (2017)	2004-2012	To examine spatial spill-over effects of attractions on tourist arrivals	China	98 admin. cities in the east of China	Panel	panel SDM	k-nearest neighbours ($k = 5$)	Either domestic or inbound tourist arrivals	domestic and international	All variables are in log (except dummies). # 4-A and 5-A rated tourist attractions (attr), # natural attractions 4A and 5A, # cultural attractions 4A and 5A, # man-made attractions 4A and 5A, GDP per capita time t-1 of destination, Foreign Direct Investment (FDI) only for inbound, # starred hotels, total length of highway, population, dummy for capital city, temporal dummy for 2008 crisis. Interaction term (attr:Wattr)	WY WX
Xu et al. (2020)	1998-2016	To explore the direct and spill-over effects of haze pollution on inbound tourism demand	China	174 prefecture cities in mid-east of China	Panel	Geographically Weighted SDM	k-nearest neighbours and Inverse distance	inbound tourist arrivals	International	Deflated per capita GDP, tourism resource endowment, tourist infrastructures index, FDI, traffic development index, accessibility, tourism price	WY WX
Romão (2015)	2003-2012	space-time analysis on determinants of tourism demand	Europe	252 NUTS2 regions in Europe	Panel	spatial panel model (SARAR)	Row-normalised rook-contiguity matrix	log of nights spent at tourism accom-modations	domestic and international	# bed places, percentage of territory under ecological protection, # of World Heritage Sites (WHS)	WY We

(Continued on next page)

Table 1.1 *(continued)*

Article	Time	Research scope	Geo	Territory	Data	Method	W matrix	Y	Tour. flows	Explanatory variables	Spat. eff.
Romão and Saito (2017)	2004-2011	space-time analysis on determinants of tourism competitiveness	Europe	237 NUTS2 regions in Europe	Panel	spatial panel model (SARAR)	row-standardized rook-contiguity matrix	GVA in tourism	Domestic and international	overights spent, investment in tourism, natural resources, cultural assets (# World Heritage Sites).	WY We
Jiao et al. (2020)	1995-2018	Forecast international tourism demand	Europe	37 European countries	Panel	dynamic spatio-temporal autoregressive model	k-nearest neighbours	tourist arrivals	International	Time lag of dependent variable and errors	WY WY_{t-1} We
Broekel and Alfken (2015)	2008-2012	To assess the impact of wind turbines on tourism demand	Germany	3228 German municipalities	Panel	spatial error panel model	contiguity, 5 nearest neighbours, distance cut-off (20, 30, 50 km)	occupancy rate		number of wind turbines (WT), accommodation facilities (FACILITIES), number of inhabitants (POPULATION), total capacity of wind turbines (CAPACITY.WT), number of turbines within 20 km (WT.VICINITY), capacity of wind turbines within 20 km (CAPACITY.VICINITY).	We
Gunter et al. (2020)	Sept. 2014-June 2016	To quantify price and income elasticities of Airbnb demand	New York City	1461 Airbnb listings	Panel	spatial Durbin model (SDM)	row-standardized inverse distance	monthly occupancy rate	domestic and international	Relative average daily rate (ADR) per Airbnb listing,average daily rate of hotels, source-market weighted real GDP, spatial lag of ADR per Airbnb.	WY WX

(Continued on next page)

Table 1.1 *(continued)*

Article	Time	Research scope	Geo	Territory	Data	Method	W matrix	Y	Tour. flows	Explanatory variables	Spat. eff.
Liu (2020)	Jan. 2001- July 2016	To solve the ambiguity of a lagged dependent variable in tourism demand	Taiwan	19 cities in Taiwan	Panel	dynamic spatial panel model	queen-contiguity matrix	monthly number of domestic tourists	Domestic	Time lag of Y, population, income (per capita average monthly salary), gasoline price index (transportation costs), dummy variables for SARS and 2008-09 crisis.	WY_{t-1}
Alvarez-Diaz et al. (2020)	2011-2013	determinants of domestic tourism flows	Spain	NUTS3 Spanish provinces	Panel	Gravity model and SAR, SEM, SDM, SDEM, SLX	Queen contiguity, k-nearest (k 1 to 10), inverse distance	tourism flows (number of trips)	domestic	highways length, dummy island (1 destination is island), # theme parks at destination, # natural parks at destination, blue flag beaches at destination, GDP per capita of origin (log), level of ageing indicator at destination, population of origin (log), relative price, distance O-D, precipitations	WY WX We
Marrocu and Paci (2013)	2009	Analysis of demand and supply determinants of domestic tourism flows in Italian provinces	Italy	107 Italian provinces (NUTS3)	Cross-section	Linear gravity model and Origin-Destination SAR	row-standardized contiguity matrix	log of tourism flows (arrivals)	domestic bilateral	Destination: GDP per capita, population density, accessibility, natural elements, cultural attractions, coast, beach quality, recreational attractions. Origin: per capita GDP, population density. O-D: distance, relative price.	WY

(Continued on next page)

Table 1.1 *(continued)*

Article	Time	Research scope	Geo	Territory	Data	Method	W matrix	Y	Tour. flows	Explanatory variables	Spat. eff.
Deng and Athanasopoulos (2011)	1998-2008 and 1999-2008	analysis of Australian domestic and international tourism demand	Australia	83 statistical local areas (SLAs) of Australia and 35 foreign Countries	Panel	dynamic spatial panel O-D model. (anisotropic version for domestic tourism)	contiguity matrix	domestic nights spent and international inbound nights spent	domestic and international	GDP (origin and destination), trend, capital cities (interacted with spatial terms), additional dummies	WY
Alvarez-Diaz et al. (2017)	2016	determinants of domestic tourism flows	Spain	19 regions of Spain	Cross-section	Gravity model and SAR model based on O-D approach	contiguity matrix	number of tourist trips (intra and inter regional)	domestic	Destination: GDP per capita, blue flag beaches, museums, theme parks, natural parks, airports, island (1 if destination is an island), autonomous city (1 if destination is autonomous city). Origin: GDP per capita, population, airports, island (1 if origin is an island), autonomous city (1 if origin is autonomous city). O-D: relative price, distance.	WY
De la Mata and Llano-Verduras (2012)	2001-2007	Spatial patterns in domestic tourist flows	Spain	18 Spanish regions	Cross-section	Spatial gravity model	contiguity matrix	domestic intra and inter regional tourist trade flows	domestic	GDP destination, GVA in hotel industry of origin, beach , Island (1 if is an island), capital (1 if Madrid), interregional migration stock, distance, temperature	

(Continued on next page)

Table 1.1 *(continued)*

Article	Time	Research scope	Geo	Territory	Data	Method	W matrix	Y	Tour. flows	Explanatory variables	Spat. eff.
Pompili et al. (2019)	2012	Explore determinants of international tourism demand	Italy	110 provinces	Cross-section	Spatial Durbin model O-D	largest eigenvalue normalised inverse distance	international tourist expenditure (main interest), tourist arrivals, nights spent, average length of stay	international unilateral	population origin, GDP per capita origin, GDP per capita destination, TCI dest., museums, coastal length, mountain area, beds in tourist establishments, beds in 4 and 5 stars hotels, pop_ big (dest. with population over 1 million), airport (airports with more than 10000 passengers). O-D: relative price,distance	WY WX
Patuelli et al. (2013)	1998-2009	to explore the effects of World Heritage Sites on domestic tourism	Italy	20 Italian regions (NUTS2)	Panel	Negative binomial O-D spatial panel model	row-standardised contiguity matrix	tourist arrivals	domestic bilateral	log GDP_{t-1}, price of hotel and restaurants (log), tourism specialization in log t-2, public expenditure in recreational activities (log 2-year lag), population (log), small crime index (log 1-year lag), violent crime index (log 2-year lag), train service satisfaction index (log), cultural demand index (1-year lag in log), diffusion of theatrical and musical shows (log 1-year lag), coast unsuitable for bathing (1-year lag), de-seasoning index (1-year lag in log), distance	WX

(Continued on next page)

Table 1.1 *(continued)*

Article	Time	Research scope	Geo	Territory	Data	Method	W matrix	Y	Tour. flows	Explanatory variables	Spat. eff.
Patuelli et al. (2014)	1998-2009	the role of distance and cultural offer on Italian domestic tourism demand	Italy	20 Italian regions (NUTS2)	Panel	Negative binomial O-D spatial panel	row-standardised contiguity matrix	tourist arrivals	domestic bilateral	log GDP previous year, price of hotel and restaurants (log), tourism specialization in log 2-year lag (share of VA in tourism), public expenditure in recreational activities (log 2-year lag), population (log), small crime index (log 1-year lag), violent crime index (log 2-year lag), train service satisfaction index (log), cultural demand index (1-year lag in log), diffusion of theatrical and musical shows (log 1-year lag), number of UNESCO World Heritage Sites, Coast unsuitable for bathing (1-year lag), de-seasoning index (1-year lag in log), distance.	WX

Table 1.2: Shift-share literature in tourism

Article	Time	Research scope	Geo	Territory	Shift-share formula	Variable	Type	Perspective
Sirakaya et al. (1995)	1980-1990	Measuring tourism performance in South Carolina	USA	South Atlantic countries	Dunn (1960)	Employment in the tourism industry	No spatial	Destination
Alavi and Yasin (2000)	1988-1992	Provide policy makers with a systematic approach to tourism policy	Middle East	Egypt, Israel, Jordan, Syria	Esteban-Marquillas (1972)	International tourist arrivals from six regions of the world	No spatial	Origin-destination
Fuchs et al. (2000)	1990-1995	Investigate the role of Shift-share as diagnostic tool in tourism	Asia	Five Asian regions	Esteban-Marquillas (1972)	International tourist arrivals from six regions of the world	No spatial	Origin-destination
Sirakaya et al. (2002)	1964-1996	Explore tourism industry performance	USA	Texas	Dynamic Shift-share	Tourism employment	No spatial	destination
Yasin et al. (2004)	1992-1996	Offer policy makers insights into the dynamics of Portuguese tourism industry	South of Europe	Portugal, Spain, France, Italy, Greece	Esteban-Marquillas (1972)	Tourist arrivals from four regions of the world	No spatial	Origin-destination
Toh et al. (2004)	1995-2000 (1st stage) 1990-2000 (2nd stage)	Provide recommendations for policy makers of Singapore	Singapore	Singapore	Two-stage shift-share analysis	Stage 1: tourist arrivals from 15 countries of the world. Stage 2: tourist arrivals by purpose of visit.	No spatial	Origin-destination
Yun et al. (2007)	1995-2004	Explore spatial competitiveness of international tourism industry	East of coastal China	Six coastal provinces	Nazara and Hewings (2004)	International tourism receipts	spatial	destination
Zuo and Huang (2020)	1990-2016	Contribution of tourism productivity to economic growth	China	Zhangjiajie city	Labour productivity shift-share analysis	Labour productivity of four main sectors	No spatial	

1.3 Spatial models of tourism flows

As can be seen in Figure 1.1, the studies using a spatial perspective of the analysis of tourism demand can be classified into two main streams based on whether or not they use information on the origin and destination of tourists simultaneously. The first (on the right of Figure 1.1) consists of spatial models that include only the information on the destination of tourists but ignores their place of origin whereas the second stream of literature (on the left of Figure 1.1) takes into account both origin and destination.

Including the origin of tourists in the analysis of tourism demand is crucial because what is being analyzed are spatial flows of people moving from an origin to a destination. Therefore, information on both source and target countries are extremely important in understanding patterns of tourist flows. It should be noted that socio-economic conditions of the destination and origin are also important, since in the context of tourism the former act as pull factors, while the latter are push factors. Another reason why the origin characteristics of tourists are important is because tourists coming from the same place tend to share social and cultural values (e.g. religion, lifestyle, culture, etc.), and hence, could have similar preferences in their choice of holiday destination.

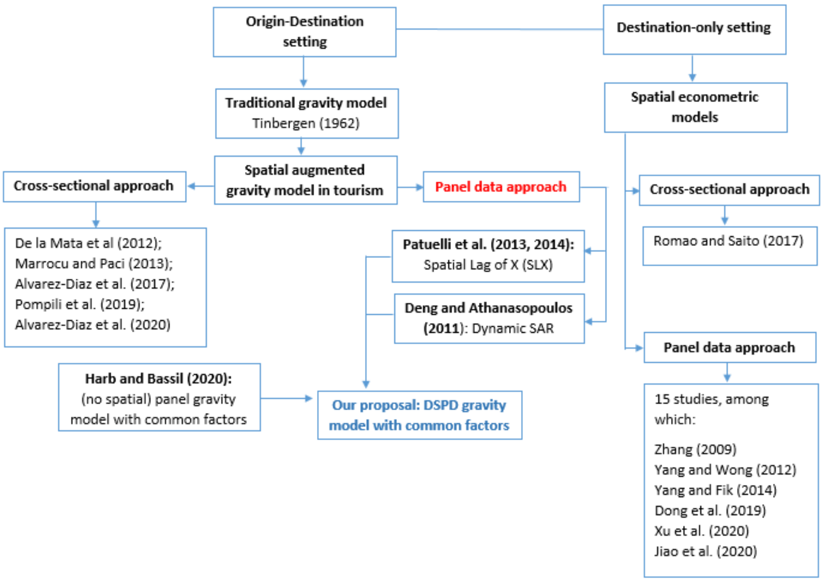

Figure 1.1: Spatial models of tourism demand

Each of the two streams of literature can be further divided into two sub-categories according to the kind of data used. The first consists of spatial models using cross-sectional data, while the second is made up of spatial models built on the basis of the traditional panel data setting. There are some advantages in using panel data over the cross-sectional setting. Spatial panel data consist of a set of spatial units (typically geographical regions) observed over time, which means they contain much more information than simple time-series and cross-sectional data, and often have fewer problems of multi-collinearity. The use of panel data increases degrees of freedom, leading to greater efficiency in the estimation of parameters. Finally, another important advantage of using panel data is that it allows more sophisticated hypotheses to be explored than a cross-sectional approach does.

As regards the importance of taking into account the characteristics of the country of origin, it is worth noting that this has been considered not only from a modelling perspective but also using other quantitative methods which have included this information in their analysis. Among those which have done so is the accounting method of Shift-Share Analysis (SSA), commonly used to decompose the source of economic change (e.g. change in employment), but, in this case, applied to tourism research. Its application in tourism is still limited, as noted by Yun and Yang (2008) in their review on shift-share analysis and its application to tourism. For an application of SSA to tourism, see Sirakaya et al. (1995); Alavi and Yasin (2000); Fuchs et al. (2000); Sirakaya et al. (2002); Yasin et al. (2004); Toh et al. (2004); Yun et al. (2007); Zuo and Huang (2020). Some studies using the shift-share technique on information on both origin and destination can be found in the literature, and most focus on international inbound tourism demand. In these studies, countries of origin take the place of the different industrial sectors in the original applications of SSA. For example, Alavi and Yasin (2000) use the Esteban-Marquillas (1972) shift-share formulation to decompose tourism demand growth in four destinations in the Middle East from six regions of origin in the world. Fuchs et al. (2000) employ the shift-share method to explore the competitive advantage of five Asian regions in attracting tourists from the six most important European and American regions in terms of tourism to Asia (i.e. South America, North America, Northern Europe, Central-Eastern Europe, Southern Europe, and Western Europe). Yasin et al. (2004) use shift-share to decompose the growth in international tourist arrivals to five European destinations (France, Spain, Italy, Greece, and Portugal) from four main areas in the world (Europe, the Americas, Eastern Asia and Oceania, Others). Toh et al. (2004) perform a two-stage shift-share analysis of the growth of tourist arrivals to Singapore. The first stage of the study consists of the decomposition of the growth of tourist flows to Singapore from 15 countries of origin from 1995 to 2000. They then compare these results with those of the main competing destinations (Thailand, Malaysia, and Hong Kong). In the second stage, the authors apply the shift-share technique to explore the components of tourist arrivals in Singapore classified by the purpose of visit where the latter takes the place of industrial sectors.

The main advantage of employing shift-share analysis within the origin-destination approach is that it enables the sources of change in tourism flows to be explored, taking into account the information on both origin and destination. Nevertheless, the spatial dimension of tourism within the shift-share approach has still been neglected. We find only one study that uses this approach Yun et al. (2007). The authors used the spatial shift-share formulation proposed by Nazara and Hewings (2004) to explore the competitiveness of Jiangsu province in China compared to neighbouring regions.

A detailed review of SSA and its development from a non-spatial to a spatial formulation will be presented in Chapter 2. In the following sub-Section, however, a description of the spatial models in the destination and origin-destination setting will be presented.

1.3.1 Destination-only setting

Spatial models that only consider the destination have been the most popular among researchers over the past decades. Indeed, more than 60% of the reviewed papers fall into this category. Most of the studies in this stream of literature employ spatial panel data, the use of cross-sectional data seems being relatively limited. Only the study by Romão and Saito (2017) analyses the spatial effects of tourism performance by using cross-sectional data from 46 prefectures in Japan for the year 2010.

Studies using spatial panel models, can be divided into two main categories on the basis of the scope of the analysis, viz., forecasting studies or explanatory and/or causal studies. The use of spatial forecasting models in tourism literature is still limited and recent. These kinds of models embed the spatial dimension in the traditional time series models to improve forecasting accuracy. In this stream of literature, the pioneering study of Yang and Zhang (2019) considers a spatial-temporal autoregressive model to forecast tourism demand in China and includes the spatial and time lag of the dependent variable (tourist arrivals). The recent paper of Jiao et al. (2020) takes another step forward by considering an autoregressive space-time model incorporating both spatial dependence and spatial heterogeneity. This model includes the time lag of both the dependent variable and errors, the spatial lag of both the dependent variable and error component and the spatial-temporal lag of the dependent variable. Both the above-mentioned studies find that incorporating spatial effects can lead to an improvement in forecasting accuracy, highlighting the importance of doing further research in this direction.

The main goal of explanatory studies, on the other hand, is to explain the complex relationships between tourism demand and its determinants, taking into account the spatial dimension of the phenomenon. Of the sampled literature, 13 papers carry out explanatory analyses. In this stream of literature, the Spatial Durbin Model (SDM) has played very a highly significant role, with 5 out of the 13 studies employing it.
The SDM includes both the spatial lag of the dependent variable and of the explanatory variables (exogenous interaction effects). The main advantage of this model is the possibility of having fully flexible spillover effects due to the inclusion of the spatial lag of explanatory variables (WX) (see Halleck Vega and Elhorst, 2015).

Another modelling specification, used in three of the papers, is the Spatial Autoregressive Combined model (SAC or SARAR). This model specification includes both endogenous interaction effects (spatial lag of the dependent variable) and interaction effects among errors. The main weakness of the SAC model with respect to the spatial Durbin model is the fact that spatial spillovers computed from this model are not completely flexible, because the spatial lag of explanatory variables is not included, and therefore the ratio between spatial spillover effects and direct effects is constant over the explanatory variables.

Some studies using simpler spatial econometric models can also be found in the literature. For example, Yang and Wong (2012), and Deng and Hu (2019) use a simple Spatial Autoregressive model (SAR) to analyze spillover effects in inbound and outbound tourism demand in China. The SAR model does not have flexible spatial spillovers thought, and the ratio between spatial spillovers and direct effects is the same for all X variables, as in the SAC model.

Another simple way to model spatial effects is a Spatial Error Model (SEM). Zhang (2009) uses a SEM to investigate the determinants of inbound tourism demand for 31 provinces in China during the years 1989-2005. However, since the SEM model only includes spatial interaction effects of errors, it does not allow the presence of spatial spillover effects to be assessed.

The use of Dynamic Spatial Panel Data models (DSPD) is still a new practice in the analysis of tourism demand with a destination perspective. The DSPD model includes the time and the spatio-temporal lag of the dependent variable (Y_{t-1} and WY_{t-1} respectively). The inclusion of this information in the model means an assessment can be made of the presence of serial dependence between observed values of each spatial unit (time effect) and the presence of spatio-temporal effects, that is the effect due to past values of the dependent variable in neighbouring regions. Liu (2020) adopts a DSPD model for solving the ambiguity of the lagged dependent variable in tourism demand literature. Resorting to the economic theories of internal and external habits, the author obtains estimations of habit persistence and word of mouth effects. As noted by the author, the word of mouth effect (external habit) has attracted little attention in tourism research. However, disregarding this effect could lead to erroneous policy conclusions and implications. As recognized by Liu (2020), the results of its study are biased due to the omission of the spatial lag of the dependent variable at the same year (WY_t). This result is a boost to further research on the word of mouth effect in tourism demand.

1.3.2 Origin-Destination setting

As stated in the introduction, since the information on the origin of tourists is very important in the analysis of the phenomenon, spatial interaction models (Origin-Destination or gravity) have been often used in the analysis of tourist flows. These models enable both demand and supply factors affecting tourism demand in a destination to be taken into account (see e.g. Pompili et al., 2019).

The spatial interaction model was proposed in the seminal work of Tinbergen (1962) for analyzing international trade flows. In this initial formulation, international trade flows between two regions depend on the economic size of the regions, and on the distance between them with an inverse law. The simplest formulation reads as follows:

$$y_{ijt} = \alpha \frac{X_{it}^{\beta_1} X_{jt}^{\beta_2}}{d_{ij}^{\beta_3}} \tag{1.1}$$

where y_{ijt} represents the trade flow between origin i and destination j at time t. X_{it} and X_{jt} are the sizes of the two regions at time t, and d_{ij} is the distance between origin and destination. e_{ijt} is the error term. Since its first application, the gravity model has attracted attention in different research fields such as trade, migration, and tourism.

The use of gravity models in the analysis of tourism is subject to the assumption that tourist flows from an origin to a destination depend on the size of the two locations and inversely depend on the distance between origin and destination.
However, the use of spatial interaction models in tourism research was criticized due to its lack of theoretical justification (Uysal and Crompton, 1984). Based on the utility theory, Morley et al. (2014) provide a theoretical background to the application of gravity models in the analysis of tourist flows. After the theoretical foundation of gravity models in the field of tourism was proposed, these models became extremely popular in tourism research (see among others, Chasapopoulos et al., 2014; Deluna and Jeon, 2014; Park and Jang, 2014; Santeramo and Morelli, 2016; Porto et al., 2018; Yazdi and Khanalizadeh, 2017; Cafiso et al., 2018; Tatoglu and Gul, 2019; Harb and Bassil, 2020).

Since the attractiveness of tourist destinations depends on different factors (e.g. natural and cultural resources, climate, transportation infrastructures, political stability, etc.), the original formulation of gravity models could not explain the complex relationship between tourism demand and its determinants. Hence, the 'augmented' version of gravity models appeared in the literature, becoming very popular in tourism economics (see among others, Khadaroo and Seetanah, 2008; Yang et al., 2010; Massidda and Etzo, 2012; Deluna and Jeon, 2014; Porto et al., 2018). The 'augmented' gravity model adds additional explanatory variables to the classical formulation to take into account the effects of demand determinants. Over the years, advanced econometric formulations have been developed, as noted by Park and Jang (2014) the most widely used being fixed effects and dynamic panel models.

Over the past two decades, gravity models have been further extended to include spatial effects and these spatial gravity models have gained increasing popularity in tourism literature. The main advantage of these models is that they can take into account the spatial dimension of the phenomenon, allowing the presence of spatial spillover effects to be identified, so that more accurate policy conclusions can be drawn.

The literature on tourism demand employing spatial gravity models can be divided into two categories, studies using cross-section data, and those using spatial panel data. The first category has attracted more attention in the literature. In the sampled literature, among the eight studies using spatial gravity models, five papers employ cross-section data. Most of the studies in this category focused on the analysis of domestic bilateral tourist flows. These consist of both intra-regional and inter-regional flows, and therefore, each geographical unit represents both origin and destination. Among cross-sectional studies, the most popular econometric specification is the Spatial Autoregressive model (SAR) with gravity structure, which accounts for only endogenous interaction effects (WY), and does not allow spatial spillovers to be flexible.
Two exceptions are Pompili et al. (2019) and Alvarez-Diaz et al. (2020). The former explores the determinants of Italian international (inbound) tourism demand using a spatial Durbin model with an origin-destination structure and cross-sectional data for the 110 Italian provinces (NUTS3 regions). One advantage of this model is that it has fully flexible spatial spillover effects. The study by Alvarez-Diaz et al. (2020) compares the linear gravity model with different spatial econometric versions (including SAR, SDM and SLX) to explore determinants of domestic tourism demand in Spain and finds that the spatial Durbin formulation outperforms the simple gravity model.

In the sample of the analyzed literature, the studies employing spatial panel gravity models are still limited and relatively recent. We find only three papers employing these models to analyze tourism demand. For example, Deng and Athanasopoulos (2011) use a dynamic spatial autoregressive panel model with an origin-destination structure to analyze both domestic and international tourism flows in Australia. The model accounts for both temporal and spatial dependence. The authors also allowed spatial dependence to be different between capital and non-capital cities. However, one limitation of this study is that spatial spillover effects are the same for all explanatory variables.

Patuelli et al. (2013, 2014) applied a Spatial Lag of the X (SLX) model within the origin-destination framework to analyze Italian domestic bilateral tourist arrivals. The authors, following Silva and Tenreyro (2006), estimate a Poisson-type model, but employing a negative binomial estimator to account for overdispersion. The SLX formulation allows for flexible spatial spillovers, but does not account for endogenous interaction effects. Therefore, since more advanced spatial econometric models with a gravity structure have been applied in the cross-sectional setting, further research is needed for spatial panel data.

This thesis aims to enrich the existing spatial literature on tourism demand modelling within the origin-destination setting from both a methodological and empirical viewpoint. From an empirical point of view, the thesis aims to explore the international tourism demand of the 110 Italian provinces in order to evaluate their ability to be competitive.

From a methodological point of view, the thesis firstly proposes a new formulation of spatial shift-share analysis to explore the spatial competitiveness effects of inbound tourism demand in the Italian provinces. The novelty of the proposed spatially extended shift-share formulation is the fact that, within a single formula, 'net' spatial competitive and allocation effects at both destination and neighbourhood level, can be assessed. The spatial competitive effects obtained from this proposal can be considered as 'net' because they take account of the influence of industrial specialization. Therefore, comparing the two spatial competitive effects, it is possible to assess the presence of spatial spillovers in tourism attractiveness, and identify the best and worst-performing destinations. A further interesting feature of this proposal is the application of spatial shift-share analysis to tourism flows with information on both the origin and destination of tourists. To the best of our knowledge, this is the first attempt to apply spatial shift-share analysis to origin-destination tourism flows.

Secondly, in line with the literature on tourism demand modelling through spatial origin-destination models, I propose a model-based approach to evaluate the ability of Italian tourist destinations to cope with the recent economic/financial crisis, the so-called 'Great recession', and to explore the determinants of recoverability from it. I therefore, propose an advanced spatial econometric panel model to analyse inbound tourism demand in the 110 Italian provinces. More precisely, a Dynamic Spatial Panel Data (DSPD) model with common factors within the gravity setting has been defined. The proposed model, at the same time, accounts for serial correlation effects (time lag of the dependent variable), spatial endogenous effects (spatial lag of the dependent), spatial exogenous effects (spatial lag of covariates), and spatio-temporal effects (spatial-temporal lag of the dependent, i.e. WY_{t-1}). This model formulation enables spillover effects to be fully flexibles. Moreover, the model includes origin and destination fixed effects accounting for the impact of factors affecting tourism demand that are fixed over time for both origin and destination, and common factors to take into account the presence of cross-sectional dependence in tourism flows. As Doran and Fingleton (2018) did for exploring the US employment, based on the 'couterfactual' prediction of tourism demand in the post-crisis period, I explore and evaluate the ability of Italian tourist destinations to cope with the crisis by using resistance and recovery measures. Finally, I assess if and how tourism resilience depends on the characteristics of a destination.

The new formulation of spatial Shift-Share Analysis and its applications will be presented in Chapter 2. Chapter 3 reports the specification and the estimations of the DSPD model and Chapter 4 defines a measure of tourism resilience, and explores its main determinants.

Chapter 2

A New Spatial Shift-Share Decomposition: An Application to Tourism Competitiveness in Italian Regions

2.1 Introduction

Shift-share analysis (SSA) is an accounting approach commonly used by regional analysts to explore the source of economic change at regional level.[1] It was initially developed to look at the change of standard economic variables like employment or value added (see, among the most recent contributions, Bianchi and Biffignandi, 2018).

Since results obtained from it have practical applications and are useful to policy makers, this tool has more recently been applied to many other fields such as productivity (Esteban, 2000; Ezcurra and Pascual, 2007; Le Gallo and Kamarianakis, 2011; Mussini, 2018), firm demography (Cheng, 2011; Espa et al., 2014; Piacentino et al., 2017b), traditional demography issues like fertility (Franklin and Plane, 2004) and migration (Plane, 1987, 1992), and tourism (Sirakaya et al., 1995; Alavi and Yasin, 2000; Fuchs et al., 2000; Sirakaya et al., 2002; Yasin et al., 2004; Yun et al., 2007).
On the basis of Dunn's seminal work (Dunn, 1960), SSA decomposes the difference

[1] The debate on the accounting approach vs. regression approach is a longstanding one. There are advantages and disadvantages to both approaches. One of the most important advantages of the accounting approach is that it can avoid imposing a given causality direction in the relationship under study, which is necessary in the regression approach. This point could be crucial when economic and social phenomena are investigated, as noted by Espa et al. (2014) in the case of business change.

in growth between each region and the national average into two components identifying whether the region is performing uniformly better than average in all industries and whether it is specialized in fast-growing sectors. Since its first application, SSA has come under fire for various reasons, leading the scientific debate towards two main lines of research. One proposes alternative methods and models within the SSA framework in order to provide a theoretical justification for shift-share analysis and to test quantitatively hypotheses about changes in the variable of interest (the so-called econometric SSA) (see Sakashita, 1973; Emmerson et al., 1975; Berzeg, 1978; Theil and Gosh, 1980; Haynes and Machunda, 1988; Marimon and Zilibotti, 1998; Toulemonde, 2001; Dogru and Sirakaya, 2017; Firgo and Fritz, 2017). The other focuses on alternative formulations of the conventional SSA in order to decompose the components of regional growth in a clearer way (see among others Esteban-Marquillas, 1972; Barff and Knight III, 1988; Nazara and Hewings, 2004; Mayor and López, 2008; Espa et al., 2014).

Our study fits into this latter stream of literature; it proposes a reinterpretation of spatial shift-share that enables the competitive and allocation effects to be computed (both components are defined below) at regional and neighbourhood level. Drawing on two of the cornerstones of SSA literature, the work of Dunn (1960) and that of Esteban-Marquillas (1972) our study proposes a refinement of spatial shift-share measures. The proposed reformulation of spatial shift-share analysis is here applied to inbound tourism in the Italian regions to investigate their competitiveness.

Although SSA is a technically simple procedure that enables us to accurately capture the underlining changes in the variable under consideration, it has not been widely used in the field of tourism (Yun and Yang, 2008) and only a few studies use SSA to explore tourist destination competitiveness (Dogru et al., 2020; Sirakaya et al., 2002; Yun et al., 2007). Among them, only the study by Yun et al. (2007) proposed and applied a spatial formulation of SSA in an investigation of the competitiveness of international tourism in Jiangsu province. This finding is somewhat surprising as spatial spillover effects in tourism are extremely clear-cut and significant. It is to be expected that tourists holidaying in a specific region are likely to spend a couple of nights visiting tourist sites in neighbouring regions. Hence, the competitiveness of a tourist destination depends on its ability to attract tourists, but also on the attractiveness of its neighbours.

Our contribution to tourism literature is in this field, focussing on tourism spatial competitiveness and providing an evaluation of competitiveness at regional level by means of a spatially extended shift-share analytical approach. This proposed formulation of spatial SSA enables tourism competitiveness at both regional and neighbourhood level to be assessed. Finally, our proposed application is interesting not only from a spatial perspective, but also from a modelling perspective because SSA is here applied to decompose spatial flows taking into account information on origin and destination.[2]

[2]Seminal works on applying SSA to spatial flow data are Plane (1987, 1992). However, these studies

To this end, we use data collected by the Italian Institute of Statistics (ISTAT) on nights spent by country of origin in Italian NUTS3 regions (i.e. provinces) between 2011 and 2014. At least to our knowledge, we are the first to apply spatial shift-share analysis to tourism demand in order to disentangle the contribution to the growth of regional tourist competitiveness and specialization from that of the neighbourhoods.[3] The analysis reveals virtuous scenarios with positive competitive and allocation effects, as well as positive spatial spillovers. About 50% of Italian tourist destinations are able to grow faster than their neighbours (i.e. positive regional competitive effect), and among them a significant number of destinations are also attractive to the international market (i.e. positive regional allocation effect).

The rest of the chapter is organized as follows. Section 2 provides a brief overview of SSA. Section 3 describes our spatial shift-share decomposition in comparison with previous versions. Section 4 includes data description, preliminary evidence and empirical results. Finally, in Section 5 some concluding remarks are reported.

2.2 Scope of the analysis: A brief overview of SSA

In Dunn's original formulation of SSA (Dunn, 1960), the change of an economic variable is decomposed into three components: the national-share to measure the contribution of the business cycle, the industrial-mix to measure the contribution of economic specialization and the regional-shift to measure that of regional competitiveness. While the interpretation of the first two components is relatively straightforward, the third is less simple to interpret. This is due to the fact that it incorporates various factors such as regional industrial specializations or influence from neighbours, viz. it cannot be seen as a net effect.[4]

To overcome these drawbacks, the literature has moved in different but not mutually exclusive directions. It has proposed decomposing the regional-shift into two subcomponents so as to isolate the influence of regional industrial specializations and thus to obtain a net measure of regional competitiveness. The most important contribution in this direction was certainly that of Esteban-Marquillas (1972). Using the concept of the homothetic variable, he measured the magnitude of a given regional economic variable assuming that the regional industrial structure was equal to the national one. The homothetic variable allows the regional-shift component to be filtered, thus obtaining a

neither embed the Esteban-Marquillas (1972) homothetic variable, nor consider the spatial structure of flows inside the shift-share decomposition. We would like to thank an anonymous Referee for their suggestion to make this aspect clear.

[3]See Yun et al. (2007) and Dogru et al. (2020) for applications of SSA framework in tourism competitiveness.

[4]This criticism of traditional shift-share analysis was highlighted by Rosenfeld as far back as 1959 when the method was first introduced to the scientific community (Rosenfeld, 1959).

net measure of regional competitiveness as well as an allocation effect measuring the ability of a region to exploit its industrial specialization.

More recently, however, the literature has endeavoured to explicitly take into account the spatial structure of data inside the shift-share decomposition. This would allow potential spatial spillovers from neighbouring regions to be measured. The first attempt in this direction was that of Nazara and Hewings (2004), who proposed a spatial version of Dunn's method.

An alternative way of controlling shift-share analysis for the neighbourhood influence was suggested by Mayor and López (2008) whose approach is based on the idea of the homothetic variable introduced by Esteban-Marquillas (1972). They measured the magnitude of a regional economic variable assuming the industrial structure of the nation and that of the neighbourhood. Specifically, they assessed the neighbourhood influence (i.e. spatial spillovers) looking at the 'size' of its economy but not at its dynamics as Nazara and Hewings (2004) had done earlier, viz. introducing the spatial structure in the regional growth rate. On the other hand, the formulation of Nazara and Hewings (2004) does not allow us to distinguish between the neighbourhood and industrial specialization effects. Both of these approaches, as we have seen, are limited in that they do not allow us to evaluate whether regional economic change is subject to neighbourhood influence or is exclusively due to regional competitiveness.

Hence, results from these two spatial formulations of shift-share analysis are not unequivocal. These problems may be avoided or at least reduced using a more recent spatial decomposition proposed by Espa et al. (2014), who propose measuring spatial spillovers by looking not only at the comparison between a given region and its neighbours but also by comparing the neighbours with the nation as a whole.
The idea is that spatial spillovers are occurring if the region performs better than its neighbours but also if its neighbours perform better than the national average. If the latter is not the case, we can conclude that regional competitive effects are occurring without any neighbourhood influence.[5]
In addition, the Espa et al. (2014) formulation enables us to explore cases in which there are some barriers (or 'regional disadvantages' as defined by the Authors) that do not allow a region to absorb positive spatial spillovers. However, although the decomposition by Espa et al. (2014) computes the competitive effect in a clearer way than the other spatial versions, it neglects the influence of industrial specializations on regional economic change.

The aim of this chapter is to rearrange and improve the formulation of Espa et al. (2014) in order to solve this problem. By means of the spatial homothetic variable, we propose a new decomposition of SSA that enables us to disentangle the competitive effect from the industrial specialization effect. Our decomposition also allows net

[5] An interesting application of Espa et al. (2014) formulation to the changes in electricity consumption can be found in Grossi and Mussini (2018).

competitive effects both at regional and neighbourhood level to be measured. Looking jointly at the two competitive effects, we are thus able to evaluate the presence of spatial spillovers related to a region with respect to its neighbours and its neighbours with respect to the nation. Furthermore, our decomposition enables allocation effects at both regional and neighbourhood level to be measured; hence, we are able to say whether a region is not only competitive but also whether it efficiently exploits its industrial specialization and, we can do the same for its neighbours. The formalization of our proposal of spatial SSA will be presented in the next section.

2.3 Spatial shift-share analysis

2.3.1 Shift-share analysis in a traditional framework

The original formulation of shift-share analysis decomposes the regional economic change into three components as follows (Dunn, 1960):

$$\Delta X_r = (X_{rT} - X_{rt}) = \sum_i X_{irt} g_n + \sum_i X_{irt}(g_{in} - g_n) + \sum_i X_{irt}(g_{ir} - g_{in}) \tag{2.1}$$

where g_n is the national growth rate; g_{ir} is the growth rate of the region r in the sector i; g_{in} is the national growth rate in the sector i; X_{irt} is an economic variable measured in the region r and in the sector i at time t.[6]

The first component, called national-share (NS), measures the influence of the business cycle on regional economic change. The second component is called the industrial mix (IM) and measures the sectoral composition effect. The third component, which is known as regional-shift (RS), measures regional competitiveness.

The main goal of shift-share analysis is to measure the contribution to regional economic change of a component specifically related to spatial features. To this end, the first two components (NS and IM) filter the regional economic change so that the regional effect (RS) is isolated.

However, the RS component cannot be seen as a net effect as it reflects many aspects that influence regional economic change. For instance, one should isolate the influence due to regional industrial specialization as well as that related to spatial spillovers in order to obtain a more accurate measure of regional competitiveness. To overcome this difficulty, different formulations of the shift-share method have been proposed.

The first important development was proposed by Esteban-Marquillas (1972), who suggested decomposing the RS into two sub-components to isolate the net competitive effect from the influence of regional industrial specialization. To this end, he introduces

[6] The growth rates (g) have been computed over the time span (t, T), where t and T are the starting and ending year, respectively.

the idea of the homothetic variable, $\hat{X}_{irt}$, which is defined as the value that X would take in region r and in sector i at time t if the regional industrial structure were equal to that of the nation:

$$\hat{X}_{irt} = \left(\sum_r X_{irt}\right) \frac{\sum_i X_{irt}}{\sum_i \sum_r X_{irt}} = \left(\sum_i X_{irt}\right) \frac{\sum_r X_{irt}}{\sum_i \sum_r X_{irt}} \tag{2.2}$$

The decomposition by Esteban-Marquillas (1972) assumes the following form:

$$\begin{gathered} \Delta X_r = \textstyle\sum_i X_{irt} g_n + \sum_i X_{irt}(g_{in} - g_n) + \\ \textstyle\sum_i \hat{X}_{irt}(g_{ir} - g_{in}) + \sum_i \left(X_{irt} - \hat{X}_{irt}\right)(g_{ir} - g_{in}) \end{gathered} \tag{2.3}$$

where g_n, g_{in}, g_{ir} are defined above. In equation (2.3), the first two components measure NS and IM effects as in the traditional approach, while the third and fourth components measure the regional net competitive effect (RC) and the regional allocation effect (RA), respectively. If RC is positive, one can conclude that regional competitive effects are contributing to regional economic change. If both RC and RA are positive, one can conclude that, in addition to regional competitive effects, regional allocation effects are also occurring. This means that regions are allocating resources in sectors where they are more successful. Therefore, RA can be interpreted as a measure of regional industrial specialization.

2.3.2 Shift-share analysis in a spatial framework

More recently, the literature has developed SSA further to explicitly consider the spatial structure of data and therefore to measure the potential influence from neighbours to regional economic change. The first such proposal was from Nazara and Hewings (2004), who suggested the following decomposition:

$$\Delta X_r = \sum_i X_{irt} g_n + \sum_i X_{irt}(\breve{g}_{ir} - g_n) + \sum_i X_{irt}(g_{ir} - \breve{g}_{ir}) \tag{2.4}$$

where:

$$\breve{g}_{ir} = \frac{\sum_s w_{rs} X_{isT} - \sum_s w_{rs} X_{ist}}{\sum_s w_{rs} X_{ist}} \tag{2.5}$$

and s identifies the neighbours of the region r. In equation (2.5), $\breve{g}_{ir}$ is the spatial growth rate, and represents the growth rate of neighbourhood of *r-th* region in the *i-th* sector; w_{rs} is an element of the row-standardized spatial matrix W in which the intensities of spatial spillovers, i.e. relations between a given region and its neighbours, are measured.[7] In equation (2.4), the first component is the traditional NS, the second measures a combined effect, and the third is interpreted by the Authors as a measure of spatial spillovers. They conclude that spatial spillovers are occurring if the third component is positive. In their view, the regional growth rate would be higher than that of its neighbours as a consequence of spatial spillovers, i.e. the ability of the region to absorb the positive influence of its neighbours.

This innovative decomposition proposed by Nazara and Hewings (2004) is however quite difficult to interpret as recently noted by Espa et al. (2014) because the third component of equation (2.4) could be positive simply as a consequence of regional advantages without any spatial spillovers; viz. the region is a good performer while its neighbours are bad performers.
Moreover, the second component measures a combined effect and for this reason its interpretation may be difficult. To overcome these drawbacks, Espa et al. (2014) propose the following spatial decomposition:

$$\Delta X_r = \sum_i X_{irt} g_n + \sum_i X_{irt}(g_{in} - g_n) + \sum_i X_{irt}(\breve{g}_{ir} - g_{in}) + \sum_i X_{irt}(g_{ir} - \breve{g}_{ir}) \tag{2.6}$$

In equation (2.6), Espa et al. (2014) split the second component of equation (2.4) to obtain two simple effects. In this way, the Authors provide a more accurate interpretation of spatial spillover effects based on the last two components of equation (2.6). The third component, that they term Neighbour-Nation Regional-Shift (NNRS), compares the neighbours of a generic region r with the nation as a whole, while the last one, the Region-Neighbour Regional-Shift (RNRS), compares the region r with its neighbours. Only if both components are positive, can one conclude that spatial spillovers are occurring. If RNRS is positive but NNRS is negative, the contribution to economic change is only due to regional competitiveness.

An alternative formulation of the spatial shift-share method was developed by Mayor and López (2008), who used a spatial homothetic variable (2.8) to assess the neighbourhood influence. They proposed the following formulation:

[7] W is an $N \times N$ spatial weights matrix whose positive elements describe the spatial relationships among the spatial units in the sample. By convention, the main diagonal elements w_{ii} are set to zero. The row-standardization is achieved by dividing each element of W by its row-sum. It leads to a matrix W with rows that sum to 1. An alternative to the row-standardization is the matrix standardization, where each element of W is divided by its largest eigenvalue (ω_{max}). The main advantage of this latter procedure is that the mutual proportions between elements of W matrix remain unchanged. The matrix standardization is usually used in the case of inverse distance matrices, because row-standardization of inverse distance matrix (i.e. weights sum to 1) would cause this matrix to lose its economic interpretation of distance decay.

$$\Delta X_r = \sum_i X_{irt} g_n + \sum_i X_{irt} (g_{in} - g_n) + \\ \sum_i \hat{X}^*_{irt} (g_{ir} - g_{in}) + \sum_i \left(X_{irt} - \hat{X}^*_{irt} \right) (g_{ir} - g_{in}) \tag{2.7}$$

where:

$$\hat{X}^*_{irt} = \sum_i X_{irt} \frac{\sum_r X^*_{irt}}{\sum_{i,r} X^*_{irt}} \qquad \text{with} \qquad X^*_{irt} = \sum_s w_{rs} X_{ist} \tag{2.8}$$

In equation (2.7), the third component measures the spatial competitive net effect (SCNE) and the fourth is called by the Authors spatial locational effect (SLE). In equation (2.8), the expression on the left is the spatial homothetic variable, and represents the extent the *i-th* sector in region *r* if the industrial composition of region *r* were comparable to its neighbours. The expression on the right is the spatial lag of the analysed variable.

In this formulation, the presence of spatial spillovers is investigated by comparing the value of the spatial competitive net effect with that of the competitive net effect obtained by the decomposition of Esteban-Marquillas (1972). The assumption is that spatial spillovers depend on the magnitude of the economy in the neighbourhood but not on its dynamics, i.e. the growth rate, as assumed by Nazara and Hewings. For these reasons, this spatial approach is introduced by the same Authors as an alternative to that of Nazara and Hewings (2004). Both approaches, however, do not allow for a direct comparison between the contribution to economic change due to regional competitiveness with that related to neighbourhood influence. If this comparison could be made it would enable us to address important research questions in regional science such as the presence of regional barriers which absorb spatial spillovers. The value of this can easily be observed in the interpretative scheme provided by Espa et al. (2014). From a regional science perspective, their approach seems to be more informative than the others. However, it is not devoid of criticism. The most important is that spatial competitive effects are influenced by corresponding industrial specialization effects, i.e. they cannot be like net effects.

2.3.3 Shift-share analysis in a new spatial framework

In the light of the aforementioned considerations, our contribution aims to extend the decomposition by Espa et al. (2014) in order to measure, within a single equation, spatial competitive net effects and, at the same time, spatial allocation effects. We propose then the following decomposition:

$$\Delta X_r = \underbrace{\sum_i X_{irt} g_n}_{NS} + \underbrace{\sum_i X_{irt} (g_{in} - g_n)}_{IM} +$$

$$\underbrace{\sum_i \hat{X}_{irt} (\breve{g}_{ir} - g_{in})}_{NNCE} + \underbrace{\sum_i \left(X_{irt} - \hat{X}_{irt}\right)(\breve{g}_{ir} - g_{in})}_{NNAE} + \tag{2.9}$$

$$\underbrace{\sum_i \hat{X}^*_{irt} (g_{ir} - \breve{g}_{ir})}_{RNCE} + \underbrace{\sum_i \left(X_{irt} - \hat{X}^*_{irt}\right)(g_{ir} - \breve{g}_{ir})}_{RNAE}$$

In equation (2.9), the first two components are the National-Share (NS) and the Industrial-Mix (IM), as in the original formulation. The third and fourth components measure the net Neighbour-Nation Competitive Effect (NNCE) and the Neighbour-Nation Allocation Effect (NNAE), respectively.[8] If NNCE is positive, it means that neighbours of region r outperform the nation as a whole, independently of their industrial specializations. If both NNCE and NNAE are positive, it means that the neighbours are also performing well in terms of the allocation of economic resources. In other words, neighbouring regions have specialized growth sectors. Therefore, we would conclude that region r can benefit from the presence of neighbours with competitive and allocation advantages. Similarly, we can interpret the last two components as net Region-Neighbour Competitive Effect (RNCE) and Region-Neighbour Allocation Effect (RNAE). Following Espa et al. (2014), we can conclude that spatial spillovers are occurring if both NNCE and RNCE are positive ('Net' Neighbour Advantage). If both NNCE and RNCE are negative, 'Net' Neighbour Disadvantages are occurring, whereas, if NNCE is positive (negative) and RNCE is negative (positive) we can conclude that 'Net' Regional Disadvantages ('Net' Regional Advantages) are occurring (see Figure 2.1).

In our case, we can also assert that these spatial effects are not dependent on industrial specializations but depend on other factors (e.g. infrastructures, institutions, etc.).

Although this approach could be applied to a wide variety of fields, we focus here on the case of inbound tourism in Italy. Specifically, we decompose the change over the period 2011–2014 in the number of nights spent by tourists in Italian provinces

[8]The third component of Equation (2.6) in our version is decomposed into two simpler effects, i.e. the NNCE and the NNAE: $\sum_i X_{irt}(\breve{g}_{ir} - g_{in}) = \sum_i \hat{X}_{irt}(\breve{g}_{ir} - g_{in}) + \sum_i \left(X_{irt} - \hat{X}_{irt}\right)(\breve{g}_{ir} - g_{in})$. Similarly, the fourth component of Equation (2.6) is decomposed into the components RNCE and RNAE.

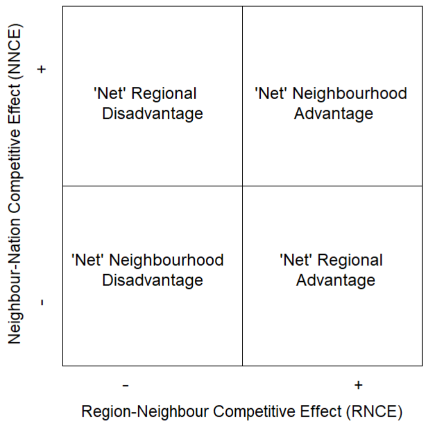

Figure 2.1: Spatial Effects

(i.e. NUTS3 regions) and consider tourists' countries of origin as different industries. Therefore, we interpret the allocation effect as the ability of a region to attract a large amount of tourism from countries of origin where there is strong growth towards that region. If both RNCE and RNAE are positive, we then conclude that a region is not only competitive in tourism with respect to its neighbours but is also highly specialized in tourism.[9] We define these regions as *Best Performers* (BP), i.e. regions that are not only competitive in tourism but are also able to allocate resources in a more effective way. This could be the case of destinations that are in the development or consolidation stages of the life cycle. If RNCE is positive but RNAE is negative, we are observing a region that is growing in tourism but is still not established; viz. it is in the involvement stage. We define these regions as *Potential Best Performers* (PBP) (see Figure 2.2).

If RNCE and RNAE are both negative, we consider them as *worst performers* (WP), while if RNCE is negative but RNAE is positive, they are classified as *Potential Worst Performers* (PWP); these will doubtless be regions which try to attract tourists from countries where they are not competitive. We can interpret the neighbourhood components NNCE and NNAE in a similar way. Hence, our proposal enables us to explore attractiveness and potential spatial advantages of Italian tourist destinations. Data description, preliminary analysis and empirical application will be presented in the next section.

[9]This means that a region specializes in those countries of origin which are highly attracted by its destinations.

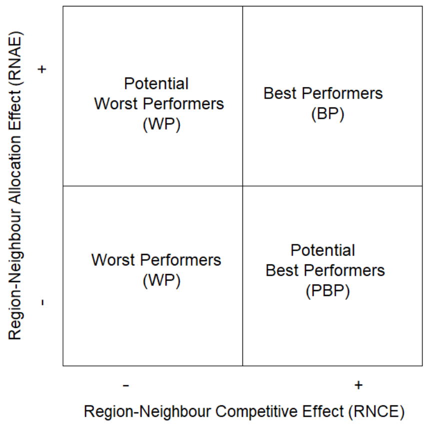

Figure 2.2: Regional Performance

2.4 Tourism Competitiveness of Italian Destinations

2.4.1 Setting of the Study and Data

Tourism is one of the most important economic sectors in Italy. At 82.833 billion euros, the value added by the tourist industry in 2010 was 6% of the total, as it was in 2015, although the monetary value was greater at 87.823 billion euros (ISTAT, 2012, 2017).[10] As far as internal tourism expenditure is concerned, there was an increase of 19.8% mainly due to domestic tourism, although the percentage of expenditure of inbound tourism increased by about 7% rising from 25.7% in 2010 to 32.9% in 2015.

For the vast set of its natural and cultural resources as well as its gastronomic heritage, Italy is a very attractive destination with a strong international identity. However, although Italy is among the top-ten competitive destinations at world level (WEF, 2017), not all Italian regions are equally able to exploit tourism as growth potential factors (OECD, 2011). Thus, regional tourist competitiveness disparities could be a threat to the competitiveness of the Italy brand.

In the light of this, it is essential to assess the competitive ability of Italian regions disentangling their competitiveness (i.e. net competitive effect) from national and neighbourhood influences. Focusing on inbound tourism, we apply our formulation of spatial shift-share decomposition to explore the change of tourist flows in Italian destinations looking specifically at the role of spatial and industrial effects at both regional and neighbourhood level.

In line with the empirical literature on regional tourism growth and tourism flows

[10]The Italian Tourism Satellite Account (TSA) was carried out, for the first time, by the Italian Institute of Statistics (ISTAT) in 2012 and then in 2017. The data refers to the tourist industry in 2010 and 2015, respectively.

(Marrocu and Paci, 2013; Yang and Wong, 2013; Yang and Fik, 2014), an important and original feature of our empirical analysis is that we explore regional competitiveness taking spatial considerations into account.

Our study uses the nights spent at tourist accommodation establishments as a measure of economic outcome. Data is provided by the Occupancy of Tourist Accommodation Establishments survey carried out by the Italian Institute of Statistics. This monthly survey collects data on arrivals and nights spent by residents and non-residents at tourist accommodation establishments in Italy.[11] Our analysis focuses on nights spent by foreign tourists in Italian provinces (i.e. NUTS3 regions) during the period 2011–2014.[12] The analysis has been performed on all the inbound tourism in Italy, paying particular attention to the following countries of origin: Austria, France, Germany, The Netherlands, United Kingdom, Russia, Switzerland and Liechtenstein (Switz-Liech). Additionally, we aggregated the other European countries in the category 'rest of Europe' (R_EU), and the other countries in the world in the category 'rest of the world' (R_WRLD). Nights spent per capita were considered in order to control for differences in absolute size among destinations for each country of origin.[13] Countries of origin of tourists here are taken as the equivalent of industries in the traditional setting of shift-share.[14]

2.4.2 Descriptive analysis

Table 2.1 shows that in Italy between 2011 and 2014 there was a 6.6% increase in inbound nights spent. Looking at the percentage change (last column in Table 2.1) we observe an increase in all countries of origin except Austria and The Netherlands. In both years, most foreign tourists come from Germany (about 31%) and the rest of Europe (about 22%).

Figure 2.3 shows the spatial distribution of absolute variations of nights spent in the period 2011-2014 across Italian NUTS3 regions. Notwithstanding a certain degree of heterogeneity across space, we can observe a cluster of regions located in the North-East with the highest levels of variation (darker areas). We also note clusters of regions with high values in the two main Italian islands, Sicily and Sardinia.

This evidence indicates the presence of a spatial pattern in the data. To explore

[11] Data are available on the ISTAT web site at http://dati.istat.it.

[12] The time-span covered by the analysis has been chosen within the limits of the availability of comparable data. Moreover, it is far enough away from the beginning of the Great recession, for our analysis not to be affected by important shocks on tourism demand. We imputed data of provinces of *Rieti* and *Viterbo* in 2014 because the Italian Institute of Statistics (ISTAT) replaced missing or unreliable data with the last available year (2011).

[13] Origin countries have been aggregated in order to prevent misleading or inaccurate results when small changes in a single country may lead to high relative changes in countries of origin or destinations of low attractiveness.

[14] This approach is similar to that followed by Fuchs et al. (2000).

Table 2.1: Per capita inbound nights spent (PINS) in Italy by origin during 2011-2014

Country of Origin	2011 PINS	2011 (%)	2014 PINS	2014 (%)	Change (%)
Austria	17651.67	5.52	17538.40	5.14	-0.64
France	23862.82	7.46	25856.81	7.58	8.36
Germany	98604.24	30.84	103067.47	30.23	4.53
Netherlands	22573.64	7.06	21652.67	6.35	-4.08
United Kingdom	17771.79	5.56	19449.28	5.70	9.44
Russia	10271.32	3.21	14374.45	4.22	39.95
Switz-Liech	19603.18	6.13	22851.64	6.70	16.57
R_EU	70501.14	22.05	73014.14	21.42	3.56
R_WRLD	38919.73	12.17	43126.68	12.65	10.81
Total	319759.53	100.00	340931.53	100.00	6.62

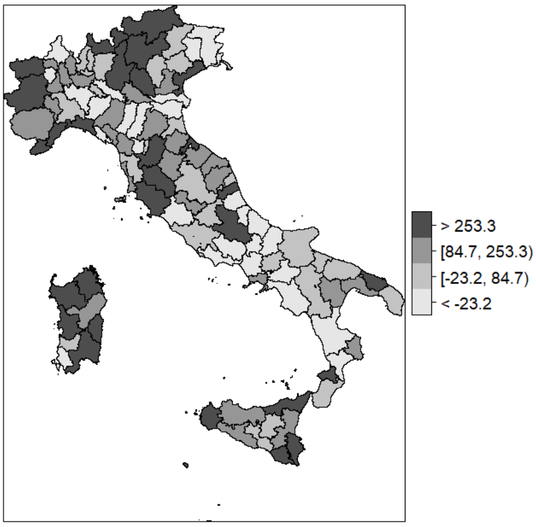

Figure 2.3: Spatial distribution of absolute variations in per capita inbound nights spent in Italian NUTS3 regions over the period 2011-2014

spatial dependence in tourist flows, we carry out an explanatory spatial data analysis (ESDA). Moran's I index of global spatial autocorrelation (Moran, 1950) and the corresponding test have been calculated. Specifically, we use a row standardized distance-based weight matrix and consider a grid of increasing cut-off distances starting from the minimum distance to ensure at least one neighbour for each region.[15]

From Table 2.2,[16] we note strong evidence of spatial dependence in the variation of nights spent. Thus, it is reasonable to think that spatial spillovers may have a positive influence on the regional variation of tourist flows. This supports the idea that the spatial structure of data in the shift-share decomposition should be explicitly considered so that tourist competitiveness can be explored.

2.4.3 Empirical results

In the description of the empirical results, we follow the interpretative diagrams found at the end of Section 2.3 (see Figures 2.1 and 2.2). In Appendix A, we report all the results obtained from the analysis (see Tables A.1 and A.2), while below we focus only on the most relevant ones.

Firstly, we look at the Region-Neighbour Competitive Effect (RNCE) and the Region-Neighbour Allocation Effect (RNAE). If the former is positive, we conclude that the region is more competitive in tourism than its neighbours. If the latter is also positive, we conclude that the region is both competitive and specialized in tourism. This means that tourist flows markedly increase in regions where resources to attract tourists are allocated from countries where these regions are highly competitive (i.e. *best per-*

[15]The Moran index is a global measure of the spatial autocorrelation among territorial units. The Moran index considers whether 'close'spatial units have similar values or not. It is defined as follows:

$$I = \frac{n}{\sum_j^J \sum_k^J w_{jk}} \frac{\sum_j^J \sum_k^J (x_j - \bar{x})(x_k - \bar{x}) w_{jk}}{\sum_j^J (x_j - \bar{x})^2} \tag{2.10}$$

where n is the number of territorial units (110 in our case of NUTS3 Italian regions); w_{jk} is the generic element of the spatial weight matrix W; x_j and x_k represent the value of variable x in the j-th and k-th spatial unit; $\bar{x}$ is the mean value of the variable x. The expected value of Moran's I index under the null hypothesis of no spatial autocorrelation is $E(I) = -1/(n-1)$; Moran's index suggests the presence of positive spatial autocorrelation if $I > E(I)$ and negative spatial autocorrelation if $I < E(I)$. Moran's index of global spatial autocorrelation is not bounded in the interval $[-1, +1]$ and so, we cannot have information about the magnitude of spatial autocorrelation, but only on its direction. A deeper discussion on the bounds of Moran's index has been recently provided by Tillé et al. (2018), who proposed a normalized version of Moran's index.

[16]p-values are computed referring to both the assumptions of asymptotic normality and analytical randomization on the null distribution of the Moran statistic. Moreover, using different cut-off distances, the hypothesis of no spatial autocorrelation is always rejected. In addition to Moran's I index, the Moran scatterplot also suggests a positive spatial correlation with almost 60% of regions in the quadrants High-High and Low-Low.

Table 2.2: Moran test on absolute variations in per capita inbound nights spent in Italian NUTS3 regions in the period 2011-2014

Distance cut-off (Km)	Estimates		
	I	p-value	
		norm.	rand.
75	0.17097	0.0054	0.004055
85	0.15143	0.004457	0.003301
95	0.13719	0.003858	0.002828
105	0.12858	0.003833	0.002809
115	0.13572	0.00101	0.000672
125	0.10916	0.00358	0.002611
135	0.11870	0.001009	0.000671
155	0.10597	0.000746	0.000486

formers). If RNCE is positive but RNAE is negative, it means that a region has higher tourism flows than its neighbours but is not as specialized as they are (i.e. *potential best performers*). If RNCE and RNAE are both negative we consider this class of regions as *worst performers*. Whereas, if RNCE is negative but RNAE is positive, we classify them as *potential worst performers*; these will doubtless be regions that allocate resources to attract tourists from countries where they are not competitive.

Figure 2.4 reveals that only 21 of the 110 regions can be classified as *best performers*. These are destinations which specialize in tourism and at the same time perform better than their neighbours. This group is composed of both traditional tourist destinations, and less well-known destinations. These regions can be clustered into three main groups reflecting different types of tourism. The first group includes famous Italian cultural tourism destinations like Bologna, Naples, Rome, Venice and Verona. The second consists of traditional business tourism destinations including Genoa, Macerata, Monza-Brianza, Novara, Treviso, Asti, Varese and Vercelli. Finally, in the third group we find emerging destinations such as Arezzo, Caltanissetta, Forlì-Cesena, La Spezia, Parma, Pesaro-Urbino, Sassari and Terni.
The latter are less well-known and have often emphasized and promoted the characteristics of local communities as a crucial starting point for the development and strengthening of their attractiveness and tourism image. For example, municipalities like Cesenatico, Le Cinque Terre (Monterosso, Vernazza, Corniglia, Manarola and Riomaggiore), Alghero and l'Asinara have been important tourist attractors for the growth of tourism in Forlì-Cesena, La Spezia, Pesaro-Urbino, and Sassari respectively.

Among the 31 *potential best performers* we find two main groups. The first group is comprised of some destinations at the beginning of their life cycle, such as Ben-

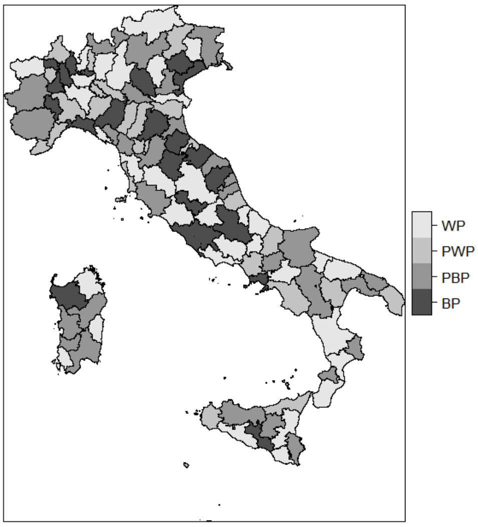

Figure 2.4: Competitive effects (RNCE) vs. Allocation effects (RNAE) at regional level.

evento, Enna, Nuoro, Oristano and Potenza and are known for their beach and/or cultural tourism. The second consists of traditional nature and/or cultural destinations such as Cagliari, Firenze, Gorizia, Grosseto, Lucca, Palermo, Syracuse and Trieste. Among these *potential best performers*, we also find some business destinations like Cuneo, Padua, Trento and Turin.
As far as this second group is concerned, it is worth noting that although they may grow faster than their neighbours, they are not able to maintain high market shares. In these cases, the negative sign of the allocation effect (RNAE) could be due to under-investment in promotion and planning for tourism. In the long run, this trend could negatively affect their competitiveness and bring them into the phase of fading popularity in the tourism product life cycle and towards the *worst performers* category. This evidence is an important outcome of our proposal of SSA, and could not be gathered from the version proposed by Espa et al. (2014). In Appendix B, which compares the regional competitive components from the two formulations (RNRS vs. RNCE/RNAE), we observe that some negative effects of regional competitiveness obtained by using the formulation of Espa et al. (2014) (RNRS, Figure a) are due to marked negative regional allocation effects (RNAE, Figure c) while the net regional competitive effect is positive (RNCE, Figure b). Similarly, some positive RNRS effects only depend on the allocation components (RNAE) but not on the net regional competitiveness component (RNCE). This is evident in the case of the lager Italian islands of Sicily and Sardinia.

There are 33 regions where both RNCE and RNAE are negative. We labelled this cluster of regions *worst performers*. This is a varied group with well-known cultural and/or coastal or mountain destinations and a significant number of business destinations too including Milan, Bergamo, Como, and Pavia. Among mountain destinations, we find some traditional skiing areas viz. Aosta and Bolzano. As for the nature tourism and cultural destinations, we could mention places like Agrigento, Latina, Pisa, Pescara, Ragusa and Viterbo. These are appealing local brands of the Italian tourist product with important regional attractors like the Valle dei Templi in Agrigento, the Leaning Tower of Pisa in Pisa, the Parco Nazionale del Circeo in Latina. The negative sign of competitive and allocation effects could be signalling a decline in popularity due to lack of investment. This is somewhat alarming, because it is a sign of inefficiency in the management of Italy's cultural heritage (see Cracolici and Nijkamp, 2006; Cracolici et al., 2008).

Finally, we come to the 21 *potential worst performers*. These are regions where RNCE is negative and RNAE is positive. In other words, while these regions are attractive, they are not as attractive as their neighbours. Some of these destinations are well-known tourist destinations like Belluno, Biella, Matera, Messina, Rimini, Salerno, Savona, and Trapani. Attention should be focused on whether these poor performances are of a temporary or a more permanent nature.

Figure 2.5 provides evidence on the performance of the neighbourhood. The legend of this map is similar to the previous one. If both NNCE and NNAE are positive in a region, we can classify this area as a *best performer* (darker areas in the map). Interestingly, we find *best performers* in the insular regions of Sicily and Sardinia, and in the region of Calabria in this group. These are areas where there is a group of neighbouring regions which are attractive and growing at rates higher than the national average. This phenomenon should alert regional policy makers to local policies so as to maximise the economic returns from tourism in these places. The region as a whole needs to be specialized in tourism and the tourist product should be seen by foreign tourists as regional not only local (see Cracolici and Nijkamp, 2008).

Finally, Figure 2.6 provides evidence on spatial spillovers. According to Espa et al. (2014), evidence of positive spatial spillovers is observed if a region outperforms its neighbours, who are also performing better than the nation as a whole. This means that both RNCE and NNCE have to be positive (darker areas in the map). Evidence of regional advantage, however, is observed if NNCE is negative and RNCE is positive. This is when a region outperforms its neighbours, whose performance in turn is worse than the national average (see Figure 2.1). Interestingly, we find positive spatial spillovers in the insular regions of Sicily and Sardinia. We also find some evidence of spatial spillovers in the regions of Puglia and Piemonte, in the South-East and North-West of Italy, respectively. In these areas, which are not particularly specialized in tourism, we find important competitive effects at both regional and neighbourhood level. Our analysis also shows the presence of regional advantages in some regions in the Centre and the North-east of Italy. These are well-known cultural and/or coastal destinations like Bologna, Firenze, Ravenna, Venice and Trieste. These places are highly attractive, but

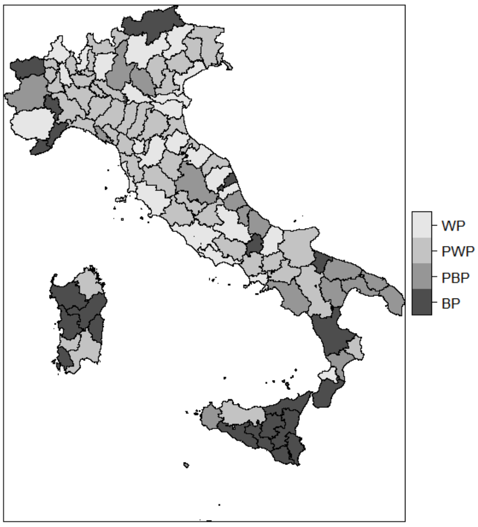

Figure 2.5: Competitive effetcs (NNCE) vs. Allocation effects (NNAE) at neighbourhood level.

their growth may be negatively affected by neighbours whose growth is lower than the national average. In these cases, regions should cooperate with each other to create policies that exploit the regional advantage of these regions to stimulate an increase in tourism in neighbouring areas.

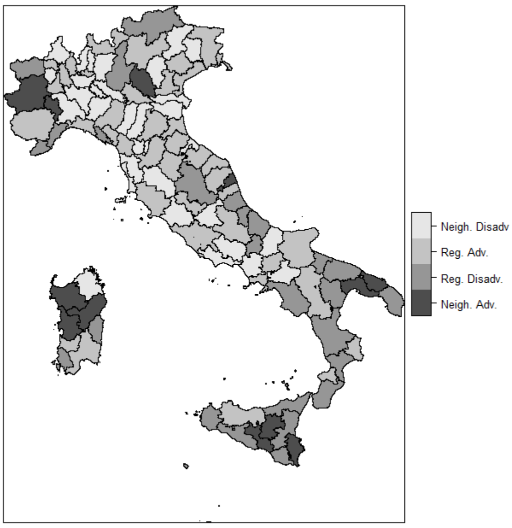

Figure 2.6: Spatial spillover effects - NNCE vs. RNCE.

Summing up, our analysis has provided a detailed picture of inbound tourism in Italy. Best and worst performers across Italian tourist destinations have been identified. Our analysis has also been able to provide evidence on tourist demand at neighbourhood level and investigate spatial spillover effects. From the empirical results, we find interesting evidence of favourable conditions in Sardinia and in some other regions in the South of the country. In these cases, tourism does not depend on single destinations, but on a number of neighbouring destinations to attract tourists. This evidence indicates the crucial role of regional tourism policy in such areas. We discovered some alarming signs of decline in some cultural destinations where unique historical and natural resources are not adequately exploited. Conversely, we find evidence of regional advantage in many cultural and/or coastal destinations in the Centre-North and in some areas in the North-east of Italy. The performance of these regions is negatively affected by the presence of unattractive neighbours. In these cases, policy makers should plan actions in stimulating a network among a single competitive region and its unattractive neighbours in order to avoid potential threats to the competitiveness of the Italy brand as a whole.

Due to the peculiarities of the tourism industry, our results are not directly comparable with the previous spatial empirical research on the Italian economy. Indeed, much of the economic debate has focused on the North-South divide (see e.g. Fazio and Piacentino, 2010; Piacentino et al., 2017b), while tourism studies usually require finer spatial scales to provide interesting insights. Economic activities in the tourism industry are often to be found in peripheral regions but not homogeneously across space. This is for example the case of the insular regions in Italy. Therefore, it would be fruitful to look at the competitiveness of different destinations within regions rather than at the disparities across regions. Our evidence contributes to this line of research in the empirical literature. However, we do find an interesting parallel to our results with those recently obtained by Di Berardino et al. (2016) on the role of structural change for regional economic convergence in Italy. The Authors of that study suggest that lagging Italian regions should move resources from less to more productive industries to encourage regional convergence. If we apply this results in our case, a structural change could be captured by the allocation components which measure the ability of regions to allocate resources to the countries of origin which are most attracted to that destination. This could favour a sort of increasing returns of regional investment in the tourism industry and thus trigger a virtuous circle of growth.

2.5 Conclusions

A new spatial shift-share decomposition is provided in this chapter to improve on the previous approaches. We exploit the idea of homothetic variables, first introduced by Esteban-Marquillas (1972) and then proposed in the spatial version by Mayor and López (2008), to extend the decomposition by Espa et al. (2014). Our proposal enables us to disentangle the sources of regional growth into more detailed components than the previous decompositions to allow us to look at the contribution to economic change of several spatial and industrial effects.

The proposed decomposition permits us to determine the net competitive effect, viz. it assesses performance in terms of growth rates independently of the industrial specialization, at both regional and neighbourhood level. We are also able to measure the allocation effect, which in our case is the ability of a region to attract tourists from countries with higher growth rates, at both regional and neighbourhood level.

Looking at these effects simultaneously, we can cluster regions as best or worst performers. The best performing regions are characterized by positive competitive and allocation effects, i.e. their industries are growing more than those of their neighbours and at the same time they are specialized in industries which have the highest growth, whereas the worst performing regions have negative values of competitive and allocation effects. Intermediate situations may occur and these are also interesting to interpret as we do in the empirical application here provided. Similarly, we are able to group neighbourhoods into best and worst performers. In the case of best performing neighbourhoods, a region could benefit from favourable surroundings if spatial spillovers are occurring. In line with the interpretative scheme suggested by Espa et al. (2014), we measure spatial spillovers jointly exploring regional and neighbourhood level competitive effects. Only if both are positive, can we conclude that spatial spillovers are occurring.

In conclusion, we believe that our proposed refinement of spatial shift-share method provides scholars with two elementary components of competitiveness and specialization, which will enable them to identify more accurately possible threats to regional competitiveness as well as opportunities especially when effects have opposite signs at regional and neighbourhood level.

An application of our decomposition to the case of tourism demand in Italian regions has also been provided in the paper. We use data collected by ISTAT on incoming tourism in Italian NUTS3 regions in 2011 and 2014. Specifically, we measure economic outcome as the nights spent by non-resident tourists and decompose regional variation in economic outcome to explore spatial and industrial effects. Some results are noteworthy. Firstly, the analysis highlights some alarming signs of decline in well-known cultural destinations where unique historical and natural resources are not adequately exploited.

Secondly, we find interesting evidence of favourable conditions in areas with important tourist attractions like the two main Italian islands. In these cases, tourism does not depend on single destinations but on a number of neighbouring places that foreign tourists can visit. In these areas we also find positive spatial spillovers. Finally, we find evidence of regional advantage in some regions in the Centre-North and in the

North-East of Italy. These are well-known tourist destinations with great tourist potential whose performance may be affected negatively by neighbouring destinations that are growing slower than the nation as a whole.

Our findings highlight the need for policy makers to focus on regional planning and the management of tourism in these areas to produce a network of single destinations among neighbouring regions. Especially in the case of regional advantages, cooperation among regions could be a suitable strategy to improve the competitiveness of regions with growth rates below the national average (see Yun et al., 2007). Useful developments in this direction include Destination Management Organizations (DMOs), which are formally constituted by regions to support tourism in local areas with a number of touristic destinations and Local Action Groups (LAGs) which perform a similar function for rural tourism.

Appendix 2.A: Spatial shift-share analysis on nights spent per 1000 inhabitants in Italian NUTS3 regions in the period 2011-2014

Table 2.A.1: Spatial and industrial results

NUTS1	NUTS2	NUTS3	Sign of Components				Profile	Spatial Eff.
			NNCE	NNAE	RNCE	RNAE		
North-West	Piemonte	Torino	+	−	+	−	PBP	Neigh. Adv.
North-West	Piemonte	Vercelli	−	+	+	+	BP	Reg. Adv.
North-West	Piemonte	Biella	−	+	−	+	PWP	Neigh. Disadv.
North-West	Piemonte	Verbano-Cusio-Ossola	−	−	−	+	PWP	Neigh. Disadv.
North-West	Piemonte	Novara	−	−	+	+	BP	Reg. Adv.
North-West	Piemonte	Cuneo	−	−	+	−	PBP	Reg. Adv.
North-West	Piemonte	Asti	+	+	+	+	BP	Neigh. Adv.
North-West	Piemonte	Alessandria	−	+	−	+	PWP	Neigh. Disadv.
North-West	Valle d'Aosta	Aosta	+	+	−	−	WP	Reg. Disadv.
North-West	Liguria	Imperia	+	+	−	+	PWP	Reg. Disadv.
North-West	Liguria	Savona	+	+	−	+	PWP	Reg. Disadv.
North-West	Liguria	Genova	−	+	+	+	BP	Reg. Adv.
North-West	Liguria	La Spezia	−	−	+	+	BP	Reg. Adv.
North-West	Lombardia	Varese	−	+	+	+	BP	Reg. Adv.

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Table 2.A.1 *(continued)*

NUTS1	NUTS2	NUTS3	Sing of Components				Profile	Spatial Eff.
			NNCE	NNAE	RNCE	RNAE		
North-West	Lombardia	Como	−	−	−	−	WP	Neigh. Disadv.
North-West	Lombardia	Lecco	−	+	−	+	PWP	Neigh. Disadv.
North-West	Lombardia	Sondrio	−	+	+	−	PBP	Reg. Adv.
North-West	Lombardia	Milano	−	+	−	−	WP	Neigh. Disadv.
North-West	Lombardia	Monza-Brianza	−	+	+	+	BP	Reg. Adv.
North-West	Lombardia	Bergamo	−	−	−	−	WP	Neigh. Disadv.
North-West	Lombardia	Brescia	+	−	−	−	WP	Reg. Disadv.
North-West	Lombardia	Pavia	−	+	−	−	WP	Neigh. Disadv.
North-West	Lombardia	Lodi	−	+	−	+	PWP	Neigh. Disadv.
North-West	Lombardia	Cremona	−	+	−	+	PWP	Neigh. Disadv.
North-West	Lombardia	Mantova	−	−	+	−	PBP	Reg. Adv.
North-East	Trentino-Alto Adige	Bolzano	+	+	−	−	WP	Reg. Disadv.
North-East	Trentino-Alto Adige	Trento	−	−	+	−	PBP	Reg. Adv.
North-East	Veneto	Verona	+	−	+	+	BP	Neigh. Adv.
North-East	Veneto	Vicenza	−	+	−	−	WP	Neigh. Disadv.
North-East	Veneto	Belluno	−	−	−	+	PWP	Neigh. Disadv.
North-East	Veneto	Treviso	−	+	+	+	BP	Reg. Adv.
North-East	Veneto	Venezia	−	−	+	+	BP	Reg. Adv.
North-East	Veneto	Padova	−	+	+	−	PBP	Reg. Adv.
North-East	Veneto	Rovigo	−	−	−	−	WP	Neigh. Disadv.

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Table 2.A.1 *(continued)*

NUTS1	NUTS2	NUTS3	Sing of Components				Profile	Spatial Eff.
			NNCE	NNAE	RNCE	RNAE		
North-East	Friuli-Venezia-Giulia	Pordenone	–	+	–	–	WP	Neigh. Disadv.
North-East	Friuli-Venezia-Giulia	Udine	–	+	+	–	PBP	Reg. Adv.
North-East	Friuli-Venezia-Giulia	Gorizia	–	+	+	–	PBP	Reg. Adv.
North-East	Friuli-Venezia-Giulia	Trieste	–	+	+	–	PBP	Reg. Adv.
North-East	Emilia-Romagna	Piacenza	–	+	–	+	PWP	Neigh. Disadv.
North-East	Emilia-Romagna	Parma	–	+	+	+	BP	Reg. Adv.
North-East	Emilia-Romagna	Reggio nell'Emilia	–	+	–	+	PWP	Neigh. Disadv.
North-East	Emilia-Romagna	Modena	–	+	–	+	PWP	Neigh. Disadv.
North-East	Emilia-Romagna	Bologna	–	+	+	+	BP	Reg. Adv.
North-East	Emilia-Romagna	Ferrara	–	–	–	+	PWP	Neigh. Disadv.
North-East	Emilia-Romagna	Ravenna	–	+	+	–	PBP	Reg. Adv.
North-East	Emilia-Romagna	Forlì-Cesena	–	–	+	+	BP	Reg. Adv.
North-East	Emilia-Romagna	Rimini	–	+	–	+	PWP	Neigh. Disadv.
Centre	Toscana	Massa-Carrara	–	+	+	–	PBP	Reg. Adv.
Centre	Toscana	Lucca	–	+	+	–	PBP	Reg. Adv.
Centre	Toscana	Pistoia	–	–	–	+	PWP	Neigh. Disadv.
Centre	Toscana	Firenze	–	–	+	–	PBP	Reg. Adv.
Centre	Toscana	Prato	–	+	–	+	PWP	Neigh. Disadv.
Centre	Toscana	Livorno	–	–	–	+	PWP	Neigh. Disadv.
Centre	Toscana	Pisa	–	+	–	–	WP	Neigh. Disadv.

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Table 2.A.1 *(continued)*

NUTS1	NUTS2	NUTS3	Sing of Components				Profile	Spatial Eff.
			NNCE	NNAE	RNCE	RNAE		
Centre	Toscana	Arezzo	−	+	+	+	BP	Reg. Adv.
Centre	Toscana	Siena	−	+	−	−	WP	Neigh. Disadv.
Centre	Toscana	Grosseto	−	−	+	−	PBP	Reg. Adv.
Centre	Umbria	Perugia	+	−	−	−	WP	Reg. Disadv.
Centre	Umbria	Terni	−	+	+	+	BP	Reg. Adv.
Centre	Marche	Pesaro-Urbino	−	−	+	+	BP	Reg. Adv.
Centre	Marche	Ancona	−	+	+	−	PBP	Reg. Adv.
Centre	Marche	Macerata	−	−	+	+	BP	Reg. Adv.
Centre	Marche	Fermo	+	+	+	−	PBP	Neigh. Adv.
Centre	Marche	Ascoli Piceno	−	−	+	−	PBP	Reg. Adv.
Centre	Lazio	Viterbo	−	+	−	−	WP	Neigh. Disadv.
Centre	Lazio	Rieti	−	+	−	−	WP	Neigh. Disadv.
Centre	Lazio	Roma	−	−	+	+	BP	Reg. Adv.
Centre	Lazio	Latina	−	−	−	−	WP	Neigh. Disadv.
Centre	Lazio	Frosinone	−	+	−	−	WP	Neigh. Disadv.
South	Abruzzo	L'Aquila	+	−	−	−	WP	Reg. Disadv.
South	Abruzzo	Teramo	+	−	−	+	PWP	Reg. Disadv.
South	Abruzzo	Pescara	+	−	−	−	WP	Reg. Disadv.
South	Abruzzo	Chieti	+	−	−	−	WP	Reg. Disadv.
South	Molise	Isernia	+	+	−	−	WP	Reg. Disadv.

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Table 2.A.1 *(continued)*

NUTS1	NUTS2	NUTS3	Sing of Components				Profile	Spatial Eff.
			NNCE	NNAE	RNCE	RNAE		
South	Molise	Campobasso	−	−	−	+	PWP	Neigh. Disadv.
South	Campania	Caserta	−	+	−	+	PWP	Neigh. Disadv.
South	Campania	Benevento	−	+	+	−	PBP	Reg. Adv.
South	Campania	Napoli	−	−	+	+	BP	Reg. Adv.
South	Campania	Avellino	−	+	−	−	WP	Neigh. Disadv.
South	Campania	Salerno	+	−	−	+	PWP	Reg. Disadv.
South	Puglia	Foggia	−	+	+	−	PBP	Reg. Adv.
South	Puglia	Barletta-Andria-Trani	+	+	−	−	WP	Reg. Disadv.
South	Puglia	Bari	+	−	−	−	WP	Reg. Disadv.
South	Puglia	Taranto	+	−	+	−	PBP	Neigh. Adv.
South	Puglia	Brindisi	+	−	+	−	PBP	Neigh. Adv.
South	Puglia	Lecce	+	−	−	+	PWP	Reg. Disadv.
South	Basilicata	Potenza	−	+	+	−	PBP	Reg. Adv.
South	Basilicata	Matera	+	−	−	+	PWP	Reg. Disadv.
South	Calabria	Cosenza	+	+	−	−	WP	Reg. Disadv.
South	Calabria	Crotone	−	+	+	−	PBP	Reg. Adv.
South	Calabria	Catanzaro	+	−	−	−	WP	Reg. Disadv.
South	Calabria	Vibo Valentia	−	−	+	−	PBP	Reg. Adv.
South	Calabria	Reggio di Calabria	+	+	−	−	WP	Reg. Disadv.
Islands	Sicilia	Trapani	+	−	−	+	PWP	Reg. Disadv.

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Table 2.A.1 *(continued)*

NUTS1	NUTS2	NUTS3	Sing of Components				Profile	Spatial Eff.
			NNCE	NNAE	RNCE	RNAE		
Islands	Sicilia	Palermo	−	+	+	−	PBP	Reg. Adv.
Islands	Sicilia	Messina	+	+	−	+	PWP	Reg. Disadv.
Islands	Sicilia	Agrigento	+	+	−	−	WP	Reg. Disadv.
Islands	Sicilia	Caltanissetta	+	+	+	+	BP	Neigh. Adv.
Islands	Sicilia	Enna	+	+	+	−	PBP	Neigh. Adv.
Islands	Sicilia	Catania	+	+	−	−	WP	Reg. Disadv.
Islands	Sicilia	Ragusa	+	+	−	−	WP	Reg. Disadv.
Islands	Sicilia	Siracusa	+	+	+	−	PBP	Neigh. Adv.
Islands	Sardegna	Olbia-Tempio	−	+	−	−	WP	Neigh. Disadv.
Islands	Sardegna	Sassari	+	+	+	+	BP	Neigh. Adv.
Islands	Sardegna	Nuoro	+	+	+	−	PBP	Neigh. Adv.
Islands	Sardegna	Oristano	+	+	+	−	PBP	Neigh. Adv.
Islands	Sardegna	Ogliastra	+	+	−	−	WP	Reg. Disadv.
Islands	Sardegna	Medio Campidano	−	+	+	−	PBP	Reg. Adv.
Islands	Sardegna	Cagliari	−	+	+	−	PBP	Reg. Adv.
Islands	Sardegna	Carbonia-Iglesias	+	+	−	−	WP	Reg. Disadv.

Table 2.A.2: Spatial shift-share decomposition

Destination	Component					
	NS	IM	NNCE	NNAE	RNCE	RNAE
Agrigento	71.75	46.29	7.04	74.98	-54.75	-25.77
Alessandria	35.42	44.87	-44.69	14.43	-17.00	14.64
Ancona	66.71	7.89	-73.31	21.76	127.10	-59.50
Aosta	567.55	472.02	1350.96	1330.98	-964.24	-1906.45
Arezzo	113.09	-14.50	-71.09	14.79	97.06	99.31
Ascoli Piceno	84.20	6.30	-35.19	-31.48	315.19	-51.08
Asti	38.40	3.48	24.91	13.07	1.37	11.24
Avellino	7.53	12.52	-17.50	0.33	-23.17	-19.39
Bari	25.73	4.92	200.05	-34.86	-28.04	-159.08
Barletta-Andria-Trani	11.58	12.89	0.04	8.58	-22.15	-6.69
Belluno	303.30	508.66	-596.59	-32.94	-129.60	23.85
Benevento	3.65	-0.60	-6.64	2.62	0.49	-1.60
Bergamo	42.56	28.89	-11.85	-12.55	-40.29	-20.06
Biella	23.51	0.50	-0.82	8.68	-82.75	2.16
Bologna	84.12	-27.07	-73.03	16.45	83.83	37.63
Bolzano	2400.15	391.82	1010.28	304.85	-1239.65	-1005.04
Brescia	299.97	-6.28	112.12	-1.47	-73.99	-16.67
Brindisi	43.92	3.99	235.70	-43.46	152.30	-39.44
Cagliari	103.95	110.70	-70.40	176.90	142.48	-146.74
Caltanissetta	5.93	9.76	0.48	1.24	20.90	17.94
Campobasso	12.31	2.26	-27.03	-3.61	-30.64	6.49
Carbonia-Iglesias	39.40	19.14	55.49	10.47	-172.02	-67.57
Caserta	18.24	-1.07	-15.33	4.00	-93.48	1.83
Catania	44.64	-17.61	149.63	30.57	-34.93	-49.44
Catanzaro	59.54	17.90	87.31	-95.03	-138.07	-50.91
Chieti	23.53	13.05	18.26	-0.27	-127.94	-5.63
Como	213.69	131.01	-56.52	-116.91	-139.79	-33.11
Cosenza	29.46	56.93	21.48	26.73	-195.69	-85.01

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Table 2.A.2 *(continued)*

Destination	Component					
	NS	IM	NNCE	NNAE	RNCE	RNAE
Cremona	19.48	23.30	-32.30	14.21	-57.46	6.55
Crotone	20.34	6.28	-72.97	55.81	103.72	-21.89
Cuneo	62.06	61.21	-28.89	-19.60	43.79	-8.09
Enna	13.68	-2.01	14.84	6.89	32.85	-33.11
Fermo	64.43	-21.21	52.23	11.59	196.72	-244.66
Ferrara	194.96	-15.96	-230.45	-32.75	-104.58	16.77
Firenze	587.40	1182.14	-509.77	-845.87	147.57	-4.89
Foggia	67.77	-15.40	-219.52	22.49	342.43	-115.97
Forlì-Cesena	173.54	240.83	-296.70	-59.19	101.81	8.98
Frosinone	49.60	37.26	-44.36	70.86	-118.38	-33.54
Genova	109.07	26.52	-87.18	24.57	171.96	35.87
Gorizia	433.17	-270.07	-847.33	650.21	263.39	-425.95
Grosseto	418.95	59.89	-216.92	-9.58	987.39	-270.43
Imperia	342.83	3.76	134.02	77.48	-250.08	78.16
Isernia	10.21	3.61	4.90	2.94	-66.10	-6.46
La Spezia	276.81	354.82	-751.34	-371.58	1466.24	45.10
L'Aquila	23.59	14.33	3.80	-10.47	-82.37	-9.53
Latina	55.85	104.79	-123.31	-40.97	-61.89	-50.75
Lecce	47.57	89.84	347.53	-92.19	-362.89	26.81
Lecco	48.64	22.48	-23.46	8.13	-32.97	11.99
Livorno	600.17	116.65	-515.02	-142.33	-228.76	370.62
Lodi	17.43	-5.00	-16.72	23.77	-34.11	14.96
Lucca	263.44	-60.63	-285.13	64.05	273.67	-26.16
Macerata	63.87	6.44	-13.01	-8.14	116.30	50.01
Mantova	20.91	6.40	-1.30	-7.37	132.95	-11.11
Massa-Carrara	66.93	11.13	-64.66	0.38	95.88	-23.44
Matera	29.19	32.78	332.38	-161.16	-248.54	226.90
Medio Campidano	14.21	23.99	-0.70	9.11	5.16	-15.31
Messina	197.40	46.33	405.10	99.41	-305.14	54.23
Milano	148.34	82.02	-134.78	130.41	-14.55	-71.61

(Continued on next page)

Table 2.A.2 *(continued)*

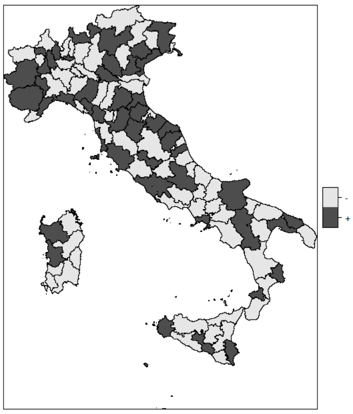
Destination	**Component**					
	NS	IM	NNCE	NNAE	RNCE	RNAE
Modena	37.57	-9.03	-32.60	10.10	-90.70	8.82
Monza-Brianza	19.41	-9.71	-13.40	20.91	23.77	20.56
Napoli	114.03	129.75	-613.43	-187.01	661.63	106.63
Novara	89.27	33.99	-65.20	-41.70	44.24	35.65
Nuoro	129.44	-33.40	164.36	63.72	113.14	-214.89
Ogliastra	456.54	342.55	72.18	768.72	-162.96	-425.58
Olbia-Tempio	820.87	1017.77	-60.20	1312.17	-385.64	-521.78
Oristano	62.23	51.96	22.79	0.77	339.18	-96.81
Padova	144.44	37.30	-102.13	33.61	93.08	-43.01
Palermo	71.96	25.73	-8.25	53.21	76.54	-99.69
Parma	54.30	-20.18	-93.41	17.86	203.90	35.75
Pavia	15.49	2.37	-6.31	7.71	-69.38	-18.41
Perugia	181.39	165.52	77.50	-63.79	-266.28	-63.68
Pesaro-Urbino	108.54	68.65	-43.51	-57.63	44.91	16.99
Pescara	42.88	70.11	5.83	-17.82	-193.69	-102.76
Piacenza	42.42	33.68	-69.85	56.07	-103.46	16.60
Pisa	259.33	72.56	-325.78	43.64	-35.07	-33.94
Pistoia	365.26	191.05	-342.50	-97.98	-562.36	45.51
Pordenone	44.92	-10.19	-33.45	43.28	-128.03	-83.80
Potenza	11.52	-3.00	-38.73	24.86	87.64	-34.17
Prato	78.34	30.16	-88.48	28.78	-61.80	38.67
Ragusa	60.67	-10.18	397.60	73.30	-38.54	-94.94
Ravenna	220.91	-31.06	-260.52	96.35	125.33	-89.96
Reggio di Calabria	11.21	14.78	4.94	9.80	-19.51	-21.29
Reggio nell'Emilia	21.21	25.43	-51.41	12.44	-111.00	14.65
Rieti	9.42	-2.04	-0.10	9.81	-21.38	-3.82
Rimini	752.48	544.78	-232.27	70.30	-969.04	159.07
Roma	297.58	-78.69	-454.41	-162.07	148.77	305.31
Rovigo	226.44	-37.33	-83.85	-19.24	-351.88	-0.43
Salerno	151.99	121.04	6.12	-206.85	-778.12	135.19

(Continued on next page)

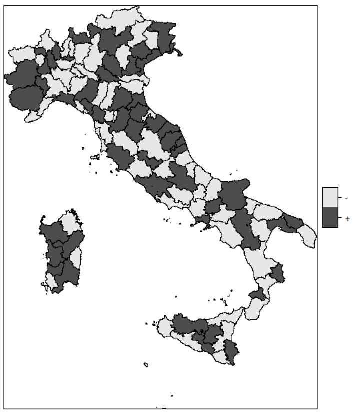
Table 2.A.2 *(continued)*

Destination	**Component**					
	NS	IM	NNCE	NNAE	RNCE	RNAE
Sassari	131.03	-69.00	141.64	141.61	138.91	41.65
Savona	271.45	54.85	22.52	37.87	-47.96	72.38
Siena	672.54	766.78	-830.13	56.36	-185.96	-43.85
Siracusa	59.55	49.84	118.70	57.22	424.08	-41.29
Sondrio	411.00	41.56	-349.51	219.02	858.15	-503.57
Taranto	13.61	9.33	84.04	-25.06	288.18	-170.65
Teramo	117.38	-6.60	205.42	-57.17	-420.78	76.55
Terni	68.15	-36.85	-43.40	22.81	96.39	133.29
Torino	21.91	16.54	6.05	-16.42	265.07	-35.48
Trapani	95.65	43.36	82.38	-3.47	-6.20	69.43
Trento	714.60	44.94	-16.24	-93.49	858.62	-15.25
Treviso	56.76	80.93	-95.25	1.96	31.01	7.82
Trieste	114.75	139.87	-336.08	123.41	105.51	-71.01
Udine	331.50	48.62	-898.72	410.05	55.79	-27.23
Varese	70.40	30.53	-61.98	12.99	123.40	13.61
Venezia	1833.20	176.75	-2863.30	-189.90	1843.41	256.40
Verbano-Cusio-Ossola	867.62	-361.54	-118.40	-439.02	-160.41	146.13
Vercelli	23.86	6.39	-8.12	8.29	63.94	2.10
Verona	744.81	8.53	162.62	-164.26	113.84	59.13
Vibo Valentia	342.19	-127.95	-414.55	-11.26	934.27	-40.81
Vicenza	47.19	53.00	-19.17	20.21	-38.97	-24.18
Viterbo	45.08	65.79	-51.03	10.09	-42.97	-54.87

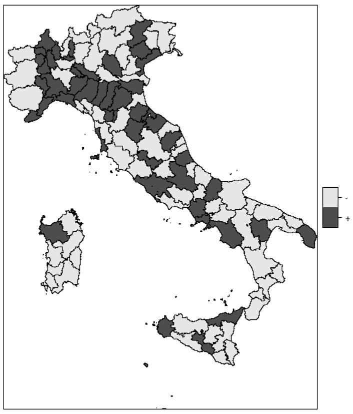
Appendix 2.B: Comparison of regional competitiveness effects between Espa et al. (2014) and our decomposition



(a) RNRS - Equation(2.6) (Espa et al., 2014)



(b) RNCE - Equation(2.9) (our proposal)



(c) RNAE - Equation(2.9) (our proposal)

Figure 2.B.1: Comaparison Espa et al. (2014) vs. our proposal

Chapter 3

Analysing Italian inbound tourism demand: A spatial gravity model approach

3.1 Introduction

The analysis of tourism demand and its forecasting is a cornerstone of tourism research which has produced a vast set of studies over the years. However, as argued in Chapter 1, the empirical literature has paid little attention to the role of space in explaining tourist flows. The spatial modelling of tourism demand has become more common only in recent years. Among others, see for example Yang and Wong (2012); Bo et al. (2017); Deng and Hu (2019); Dong et al. (2019); Xu et al. (2020).

Tourist flows can be seen as a special kind of trade in services (see e.g. Marrocu and Paci, 2013; Morley et al., 2014), where destinations and origins take the place of importers and exporters. As widely acknowledged in trade theory, the characteristics of both importers and exporters should be considered. On the basis of these considerations and the utility theory, Morley et al. (2014) provide a theoretical background to the application of gravity models – that is spatial interaction or origin-destination (O-D) models – for analysing tourism flows. One year earlier, Marrocu and Paci (2013) proposed an empirical gravity model for exploring regional tourist flows, which includes not only the basic variable of distance between origin and destination, but also spatial filters and regional characteristics of the origin and the destination in order to control for under-specification problems.

As regards spatial filters, since different types of spatial dependence can affect tourist flows due to the fact that spatial features of tourism are generally complex and do not depend only on distance, our study, in the spirit of the aforementioned stream of literature, explores unilateral inbound tourism flows in Italy from 23 European origin countries by applying a Dynamic Spatial Panel Data (DSPD) model with common factors within the Origin-Destination (O-D) framework. The analysis is performed for the 110 Italian NUTS3 regions and for the period 2004-2017.

A Dynamic Spatial Panel Data model with common factors (DSPD-WCF) has been used to explore the presence of spatial and temporal effects on Italian inbound tourism demand and its main determinants. This model simultaneously takes into account serial correlation by means of the time lag of the dependent variable, spatial endogenous effects with the spatial lag of the dependent variable, spatial exogenous effects with the spatial lag of covariates, and space-time effects with the spatial-temporal lag of the dependent variable. Moreover, the use of common factors means both weak and strong cross-sectional dependence can be controlled at the same time (for recent applications, see Halleck Vega and Elhorst, 2016; Ciccarelli and Elhorst, 2018; Elhorst et al., 2020).[1]

The DSPD-WCF used in this study, also controls for both origin and destination characteristics that are fixed over time with origin and destination fixed effects, and for spatial cointegration effects.[2] Similarly to time series, neglecting the presence of non-stationarity and cointegration in the data may lead to misleading results in spatial series too mainly due to spurious regression problems (Lauridsen, 1999).

Finally, since the time-span covered by the analysis includes the shock of the Great recession, in order to measure its effects on regional tourist demand, DSPD-WCF estimates have been used to construct a counterfactual tourist flows series for the 110 Italian provinces. This then provides a yardstick for assessing the depth of its impact and the extent of subsequent recovery in each province, controlling for both origin and destination characteristics. We use estimates from DSPD-WCF in Chapter 4 to evaluate if

[1]The concept of cross-sectional dependence (CSD) is related to the presence of correlations (dependence) across spatial units and it may arise due to the presence of spatial diffusion processes, or if spatial units respond to a common shock (e.g. oil price shock, national policies, technological shock, common currency, etc.). The concepts of weak and strong CSD have recently come out in the literature, but different definitions have been provided (Ertur and Musolesi, 2017) (Ertur and Musolesi, 2017), the former is usually associated to spatial models, while the latter to common factors (Bailey et al., 2016b) (Bailey et al., 2016). The distinction between weak and strong CSD is based on the behaviour of the largest eigenvalue of the variance-covariance matrix of cross-sectional units (see Chudik et al., 2011). Bailey et al. (2016) Bailey et al. (2016b) provided a characterization of the degree of CSD, and they represented the degree of CSD by α. This test statistic (α) lies on the interval $(0,1]$, where $\alpha = 1$ suggests strong CSD, and $\alpha \leq 0.5$ points to weak CSD. Elhorst et al. (2018) Elhorst, Gross, and Tereanu (2018) provide an explanation of the interplay between CSD, common factors, weight structure and estimation for different values of α.

[2]Spatial cointegration can be seen as the spatial counterpart of the time series cointegration, and it is related to the stationarity and stability of spatial series. Specifically, two spatial series X and Y spatial integrated of order d are said to be spatially cointegrated if there exists a linear combination of X and Y of order less than d (for more details, see Lauridsen, 1999; Yu et al., 2012) (for more details, see Lauridsen, 1999; Yu, de Jong, and Lee, 2012).

and how the ability of Italian tourist destinations to resist and recover to/from the Great recession differs across regions.

There are some novel aspects to our study that we would like to highlight. First, our contribution is the first attempt to explore inbound tourist flows accounting for spatial and temporal dependence within the origin-destination theoretical framework. The Italian case is interesting as there are few contributions based on an origin-destination model and these mainly refer to a single time-point or to specific regions. There are five studies that should be mentioned, namely Massidda and Etzo (2012), Marrocu and Paci (2013), Patuelli et al. (2013, 2014) and Pompili et al. (2019). The first four studies focus on domestic demand and the last one on inbound demand.[3] Massidda and Etzo (2012) investigate the main determinants of Italian domestic tourism demand as measured by regional bilateral tourism flows by using a GMM panel data for the period 2004-2007. The analysis was developed both at aggregate level and for two macro-areas, i.e. the Centre-North and the South. However, they do not control for spatial dependence. Marrocu and Paci (2013) analyse domestic demand for 107 Italian provinces for the year 2009 using an origin-destination (O-D) spatial interaction model. Following a bilateral gravity approach, the authors consider a vast set of explanatory variables including distance and pull and push characteristics to assess destination attractiveness. They highlight the importance of spatial dependence effects on tourism demand. Patuelli et al. (2013) investigate the impact of World Heritage Sites (WHS) on tourist flows among the 20 Italian regions by means of a spatial panel data model within the O-D setting. They find WHS produce a spatial substitution effect. Similarly, Patuelli et al. (2014) explore the role of distance in mediating the effect of cultural offer on tourism demand. Pompili et al. (2019) explore inbound demand using a unilateral gravity model involving demand and supply-side factors jointly and spatial effects.

The second novel aspect of our study is that it investigates tourism flows by carrying out an econometric analysis based on the recently proposed weak and strong cross-sectional dependence spatial econometric models (Halleck Vega and Elhorst, 2016; Ciccarelli and Elhorst, 2018; Elhorst et al., 2020). As argued by Marrocu and Paci (2013), if spatial interaction effects are neglected, it may lead to the problem of omitted variables. Furthermore, neglecting the presence of cross-sectional dependence in the data may lead to serious problems mainly related to the fact that standard panel data models estimators may provide misleading inference and inconsistent parameter estimates; and also, unit root tests for panel data models may be affected by size bias (Ertur and Musolesi, 2017).

Thirdly, a dynamic spatial Durbin specification within the origin-destination framework enables us to obtain spatial spillover effects that are straightforward in terms of interpretation because spatial endogenous (WY) and spatial exogenous effects (WX)

[3] It is worthy to notice that the earliest application of the origin-destination approach to domestic tourism in Italy was that performed by Gardini (1979).

can be measured simultaneously. This overcomes some well-known drawbacks of the Spatial Autoregressive model (SAR), which is the most widely used in the origin-destination tourist literature. Pinkse and Slade (2010, p. 106) for example, highlighted some drawbacks of this model. Among them, the fact that the spatial dependence structure is all attributed to spatial endogenous effects (WY), and the risk of endogeneity issues is noteworthy. Corrado and Fingleton (2012) show that the coefficient of WY become significant because it may embed the effect of omitted spatial exogenous effects (WX) or non-linear effects of WX. Halleck Vega and Elhorst (2015) point out that this latter drawback may make interpretation of spatial spillover effects difficult because it is not clear whether the significance of the coefficient of WY is real or is due to omitted variables.

Finally, another innovative aspect of our research is that the focus is not only on the assessment of tourist attractiveness at regional level considering origin and destination factors simultaneously, but also on the evaluation of regional tourist resilience. This aspect will be better illustrated and explored in the next Chapter.

The chapter is organised as follows. In Section 2, we provide a brief review of the literature on the main determinants of tourism demand. In Section 3 the empirical model and econometric strategy are outlined, while in Section 4 the empirical findings are presented and discussed, followed by some concluding remarks.

3.2 An overview of tourism demand and its determinants

Identifying the complex mechanisms linking tourism demand to the factors that influence it is of paramount interest in modelling and forecasting tourism demand. There are two main reasons why studying this linkage is important. The first is that the knowledge of these mechanisms enables Destination Management Organisations (DMOs) to plan more accurate policy strategies. The second is related to the fact that tourism is an important factor of economic growth, and positive effects related to tourism could foster the economic growth of other sectors (see among others, Muryani et al., 2020; De Vita and Kyaw, 2017; Chou, 2013; Sequeira and Nunes, 2008).

As noted in the comprehensive review by Song and Li (2008), tourist arrivals is the most widely used measure of demand. Some studies have also used nights spent not only to account for the number of tourists, but also for the length of stay (among others, see Brida and Risso, 2009; Garín Muñoz, 2007). Other measures of tourism demand used in the literature include tourist expenditure, tourism revenues, and tourism employment (Song et al., 2019; Song and Li, 2008). [4]

[4]To control for the different size of destinations, relative measures of the demand variable are generally

As far as the determinants of tourism demand are concerned, the empirical analysis is based on two main approaches, i.e. the demand-side and supply-side perspective, which consider the characteristics of the countries of origin and destination, respectively. Most of these studies have used time series or panel data models (for an extensive review, see Song et al., 2019).

More recently, some scholars have begun combining the two approaches by using gravity or origin-destination (O-D) models so that origin and destination factors affecting tourism flows can be considered simultaneously. The use of gravity models in tourism research was limited because of the lack of a theoretical basis for it, until Morley et al. (2014) provided a theoretical background to their use in tourism research based on utility theory. Following their study, the use of gravity models has received increasing attention in tourism literature (see among others, Chasapopoulos et al., 2014; Santeramo and Morelli, 2016; Yazdi and Khanalizadeh, 2017; Cafiso et al., 2018; Tatoglu and Gul, 2019; Harb and Bassil, 2020).[5]

In the empirical literature, among the factors affecting tourism demand, we find variables such as the income of tourists, the relative price of destination to origin, the price of competing destinations (substitute prices), travel costs, and exchange rates (Song and Li, 2008). Income is a measure of the purchasing power of tourists and is most often measured by the GDP of the country of origin. Relative prices are likely to proxy the difference between the cost of living in the destination and that in the country of origin. It is usually approximated by the ratio between the Consumer Price Index (CPI) of the destination and the CPI of the origin. Travel costs have been measured by both the price of crude oil (Brida and Risso, 2009; Garín Muñoz, 2007, 2006; Ledesma-Rodríguez et al., 2001), and the distance between origin and destination (Harb and Bassil, 2020; Xu et al., 2019). Other factors affecting tourism demand used in the literature embrace political stability (Xu et al., 2019; Liu et al., 2018; Habibi, 2017), infrastructure endowment (Barman and Nath, 2019; Chen and Haynes, 2015), promotional expenditure (Ledesma-Rodríguez et al., 2001), safety and the level of air pollution (Tang and Tan, 2016), and tourism cycles (Kožić, 2014). Some studies also include variables related to economic relations between countries, e.g. trade openness, bilateral goods trade, and foreign direct investment (Habibi et al., 2009; Liu et al., 2018; Xu et al., 2019).

Traditionally, the literature has always been careful to take into account the presence of temporal effects in tourist flows by the inclusion of the time lagged dependent variable. According to Garín Muñoz (2007), there are two reasons for including tourism demand in the previous year among the covariates. The first is related to familiarity with the destination. Indeed, one may expect that tourists are more likely to visit destinations with which they are familiar than unknown ones. Second, tourists talking about their

used, like arrivals or nights spent per capita (see among others, Tang and Tan, 2016; Garín Muñoz, 2006).

[5] Some previous original contributes are the studies by Massidda and Etzo (2012) and Marrocu and Paci (2013).

holidays spread the knowledge about a destination, and hence, increase the familiarity of potential tourists with that destination. Thus, the coefficient of the lagged dependent variable can be interpreted as a measure of habit formation. Neglecting the time lag of the dependent variable may lead to an overestimation of the effect of other explanatory variables, since these effects will involve both direct and indirect effects (Morley, 1998). A large number of empirical studies find positive and significant effect of the time lagged dependent variable, highlighting the presence of habit effects in tourism (see among others, Habibi, 2017; Rodríguez et al., 2012; Brida and Risso, 2009; Garín Muñoz, 2007).

Recently, the literature has also been looking at the role of space in describing tourism flows since the inclusion of the spatial dimension provides information about the presence of spatial dependence (e.g. spatial endogenous effects) and enables direct and spatial spillover effects of covariates to be computed. Indeed, Marrocu and Paci (2013) argue that neglecting spatial spillover effects may lead to the usual omitted variables estimation problem, and hence, gravity estimates may suffer from an upward bias. They highlight that the distinction between the relative effects of internal and external determinants of tourist flows is a further advantage of including spatial dependence because it means that more accurate policy strategies can be drawn up.

3.2.1 *A spatial perspective of tourism demand*

Empirical studies on the spatial perspective of tourism demand can be divided into two main groups. The first consists of studies that only take into account either information on the origin (demand-side approach) or the destination (supply-side approach) of tourists (see among others, Xu et al., 2020; Deng and Hu, 2019; Dong et al., 2019; Liu, 2020; Yang and Wong, 2012). The second group, using a gravity or origin-destination approach, considers the characteristics of both origin and destination among the factors affecting tourism demand (see among others, Alvarez-Diaz et al., 2020; Marrocu and Paci, 2013; Patuelli et al., 2013; Deng and Athanasopoulos, 2011).

As regards the first group, the analysis is generally based on tourist arrivals and concerns mainly international tourism (Xu et al., 2020; Jiao et al., 2020; Yang and Zhang, 2019). Empirical studies within this group approached the inclusion of spatial effects in different ways. One of these ways is the inclusion of the spatially lagged dependent variable, which has attracted a lot of attention as a method of controlling spatial endogenous effects. In most cases, the coefficient associated with the spatial lag of the dependent variable is found to be positive and significant (see e.g. Xu et al., 2020; Deng and Hu, 2019; Yang and Wong, 2012). Other spatial effects often used are the spatial lag of explanatory variables (Xu et al., 2020; Dong et al., 2019; Bo et al., 2017), and the spatial-temporal lag of the dependent variable (Jiao et al., 2020; Yang and Zhang, 2019; Liu, 2020). The inclusion of spatially lagged explanatory variables (i.e. exogenous interaction effects) increases the flexibility of spatial econometric models in measuring spatial spillover effects. The Spatial Lag of X (SLX) model is the simplest model allowing flexible spatial spillover effects (Halleck Vega and Elhorst, 2015) and they argue that spillover effects from this model are more straightforward to estimate and interpret than those from the widely used spatial econometric models that do not include exogenous interaction effects (SAR, SARAR, SEM). Another advantage of including the spatial lag of explanatory variables is that endogenous regressors can be tested without resorting to spatial econometric techniques. Therefore, they suggest considering the SLX model as the starting point in the selection of a model when a well-founded theory suggesting the most appropriate model is lacking.

As regards the analysis of tourism demand based on the origin-destination approach, the empirical literature using spatial effects is still very limited. Among the few studies, the most commonly used spatial effects are the spatially lagged dependent variable (Alvarez-Diaz et al., 2020, 2017; Marrocu and Paci, 2013; De la Mata and Llano-Verduras, 2012; Deng and Athanasopoulos, 2011) and the spatial lag of explanatory variables (Alvarez-Diaz et al., 2020; Patuelli et al., 2014, 2013). Almost all the studies in this stream of literature focused on domestic tourism, measured by bilateral tourist arrivals, i.e. each region represents both origin and destination. An exception is the article by Deng and Athanasopoulos (2011) which analyses domestic bilateral tourist flows as well as international unilateral flows (region of origin is different from region of destination) with two different models.

Generally, gravity models with spatial effects are performed on cross-sectional data, and few studies consider spatial panel data (see Patuelli et al., 2014, 2013; Deng and Athanasopoulos, 2011).

As far as cross-sectional studies are concerned, De la Mata and Llano-Verduras (2012) analyze domestic bilateral flows among 18 Spanish regions in the years 2001 and 2007. Differently from other studies in the literature, they compute a measure of tourist expenditure based on tourist trade flows, instead of tourist arrivals. The authors use a Bayesian Spatial Autoregressive model (SAR) and find a significant positive effect of GDP of destination and Gross Value Added (GVA) of the hotel industry in the origin. They also include some characteristics of the origin like beach length and temperature. Finally, the authors find positive spatial endogenous effects, and a negative effect of distance.

Marrocu and Paci (2013) explore demand and supply determinants of domestic bilateral tourist arrivals in the Italian NUTS3 regions in 2009. The authors use an extended spatial autoregressive specification as suggested by Le Sage and Pace (2009, 2008). More specifically, starting from the assumption that tourist flows may be simultaneously affected by two kinds of spatial dependence, one arising from the demand side (origin) and the other from the supply side (destination), they disentangle the spatial endogenous effects into three effects, based on their source. One of these catches the part of dependence due to the interaction between neighbouring countries of origin. A second captures the share of dependence arising from the fact that tourist flows from an origin to a destination may produce similar flows in neighbouring destinations. The third one is the interaction between the first two effects and is called *'origin-to destination'* dependence by Le Sage and Pace (2008). Marrocu and Paci (2013) find significant effects of both origin and destination determinants, along with evidence of origin and destination spatial effects. However, their approach neglects the presence of possible spatial exogenous effects (WX), which may lead to problems due to omitted variables, as Corrado and Fingleton (2012) point out.

Alvarez-Diaz et al. (2017) analyze the main determinants of domestic bilateral tourist flows in 19 regions of Spain in 2016. The authors employ a Spatial Autoregressive model (SAR) with an origin-destination structure and find evidence of positive spatial spillovers effects. They also find a negative effect of distance between origin and destination and a positive influence of the level of wealth of destination, in addition to positive income elasticity. Moreover, the authors find that the characteristics of a destination (including beach quality, accessibility, number of museums and parks) have positive effects on Spanish domestic tourism demand. Although their study accounts for spatial endogenous effects (WY), it does not take into account both dynamic effects and spatial exogenous effects (WX).

Alvarez-Diaz et al. (2020) take a step forward with respect to the study by Alvarez-Diaz et al. (2017) focusing on the determinants of bilateral domestic tourist flows in Spain at Nuts3 level, and taking into account spatial exogenous effects. The authors compare results from different spatial econometric models with origin-destination structure applied to averaged tourist flows between 2011 and 2013. They find that the Spatial Durbin Error model (SDE) and the Spatial Error Model (SEM) produce the best fitting. From the empirical point of view, Alvarez-Diaz et al. (2020) find evidence of positive effects of tourist flows in neighbouring regions and a negative effect of the spatial lag of the number of theme parks and natural parks. Furthermore, they find a positive effect of length of highways, blue flag beaches, number of theme and natural parks of destination, in addition to positive income elasticity and a positive effect of population density of the region of origin. Finally, Alvarez-Diaz et al. (2020) also find a negative effect of rainfall of destination, and a negative influence of relative price and distance. Although their study takes into account spatial exogenous effects (WX), it does not account for dynamic effects of the phenomenon, because they consider static models.

Differently from the above-mentioned studies, Pompili et al. (2019) focus on international unilateral tourist flows in the Italian NUTS3 regions from 20 countries of origin, and use tourist expenditures, arrivals, nights spent, and length of stay as dependent variables. They applied a Spatial Durbin Model (SDM) specification and find a significant positive spatial autoregressive coefficient in all cases, indicating that a destination benefits from the presence of attractive destinations in the neighbourhood. Although they included WX in the model, they did not account for dynamic effects because they estimated the model in a cross-sectional setting.

As far as panel data is concerned, Patuelli et al. (2013) explore the effects of World Heritage Sites (WHS) on Italian domestic tourism demand, measured by bilateral tourist arrivals among the 20 Italian regions (NUTS2) for the period 1998-2009. The authors estimate a Spatial Lag of X model (SLX) using a negative-binomial estimator to account for overdispersion in the data. They find significant effects of WHS in a destination and in its neighbourhood, along with significant effects of other determinants, such as cultural demand, the diffusion of cultural events, the price of hotel and restaurants, and the level of crime.

Patuelli et al. (2014) use a negative-binomial SLX model to explore the role of distance and cultural offer on domestic bilateral tourist arrivals in Italy for the period 1998-2009. They find that cultural offer affects the willingness to travel, and that this effect varies with geographical distance.

Deng and Athanasopoulos (2011), using a dynamic spatial autoregressive model, carried out a complex study of Australian domestic and inbound tourism demand. The authors considered a panel of quarterly data for the period 1998-2008 in the case of domestic bilateral flows, and 1999-2008 in the case of unilateral international tourist flows. The model takes into account both temporal and spatial effects, which are allowed to differ between capital and non-capital cities and to account for the seasonality effect. The authors found a significant positive effect of income of origin, along with significant spatial and temporal effects in the case of domestic tourism. In the case of international inbound tourism they found positive temporal effects and significant spatial effects, along with temporal dummies for two one-off events, the Bali bombing and the Sidney Olympic Games.[6]

Although the study by Deng and Athanasopoulos (2011) makes an attempt to control for habit persistence formation in tourist flows by estimating a dynamic SAR spatial panel gravity model, it does not account for the presence of exogenous spillover effects (spatially lagged covariates). Indeed, the SAR specification is not able to separate the causes of spillover effects, and hence, if the effect on tourist flows in one destination due to neighbouring regions is due to their endowment resources or to their level of tourist flows (Pompili et al., 2019). To overcome this issue Halleck Vega and Elhorst (2015) and Elhorst and Halleck Vega (2013) suggested including the spatial lag of explanatory variables. However, only a few articles have considered this suggestion in tourism stud-

[6] Among other influencing factors of tourist flows frequently used within the spatial literature on tourism demand, we mention recreational attractions (Patuelli et al., 2013, 2014; Marrocu and Paci, 2013), tourism specialization, the petty crime index, violent crime, diffusion of theatrical and musical shows, coasts unsuitable for bathing (Patuelli et al., 2013, 2014), and rainfall (Alvarez-Diaz et al., 2020). Other examples of explanatory variables are population of origin, accessibility (length of highways, number of airports, train satisfaction index), natural resources (number of natural parks, blue flag beaches, theme parks), cultural resources (number of UNESCO World Heritage Sites, museums, etc.).

ies employing spatial gravity models (Alvarez-Diaz et al., 2020; Pompili et al., 2019; Patuelli et al., 2014, 2013).

In the light of that, our study, using a gravity model framework, analyzes inbound tourism flows by applying an advance in static spatial panel approach, namely the so-called Dynamic Spatial Durbin model with common factors, which enables us to model tourism flows taking into account both time-dependency in spatio-temporal series, and weak and strong cross-sectional dependence. A Dynamic Spatial Panel Data model enables us to better interpret the role of spatial spillover effects in inbound tourism demand considering both the effects due to determinants of destinations and those related to the attractiveness of neighbouring regions, accounting for both temporal and spatial dynamics, along with the presence of cross-sectional dependence. Full details on the methodology are provided in the next section.

3.3 Data and Model

3.3.1 Data description

The study focuses on unilateral tourism demand in the 110 Italian destinations (NUTS3 regions) from 23 countries of origin during the period 2003-2017; thus, a panel of 110*23*15 observations has been considered. We measure inbound tourism demand of Italian destinations by means of nights spent by non-residents in Italian tourist accommodation establishments. The data are provided by the Occupancy of Tourist Accommodation Survey carried out by the Italian Institute of Statistics (ISTAT).[7] To control for different regional size of the phenomenon, nights spent per capita have been considered as the dependent variable.

Data on tourism flows are not homogeneous over the period of analysis due to changes in the number of Italian provinces (NUTS3 regions). Before 2009 there were 103 of them, then four new provinces were created in Sardinia (*Carbonia Iglesias*, *Medio Campidano*, *Ogliastra*, *Olbia-Tempio*), one in Lombardy (*Monza e Brianza*), one in Marche (*Fermo*), and one in Apulia (*Barletta-Andria-Trani*) making a total of 110. In 2016, the four provinces of Sardinia added in 2009 were replaced by the province of *Sud Sardegna*. These changes in the definition of provinces create some problems of data comparability. To overcome that, we considered the NUTS3 configuration with 110 provinces, and we imputed data for missing provinces based on the area of the municipalities that moved from the old provinces to the new ones. What we did was to compute the total area of municipalities that formed the new province, then compute the portion of area that formed the new province. Thus, we impute the new province with a share of tourism flows proportional to its area.

[7]Data are accessible at the following website: http://dati.istat.it.

As far as the explanatory variables are concerned, on the basis of the empirical literature, we consider two traditional variables widely used in the gravity models of tourism demand, i.e. distance and relative price. Additional variables of determinants of tourism demand have been included based on data availability at NUTS3 level for all the period of analysis. Distance is the geographical distance between each origin and destination pair in kilometres.[8] This variable is included in many studies on domestic and international tourism demand as a proxy of travel costs and time (see among others Khadaroo and Seetanah, 2008; Massidda and Etzo, 2012; Marrocu and Paci, 2013; Patuelli et al., 2013, 2014; Pompili et al., 2019). The effect of distance on international tourism demand is expected to be negative. As regards the price variable, it is computed as the ratio between the consumer price index (CPI) of each destination and that of each origin. This variable captures the effect on tourism flows of the discrepancy in living conditions between destination and origin. Many empirical studies on international and domestic tourism demand include a measure of relative prices, highlighting its relevance in the analysis of tourist flows (see among others Massidda and Etzo, 2012; Marrocu and Paci, 2013; Chasapopoulos et al., 2014; Alvarez-Diaz et al., 2017; Yazdi and Khanalizadeh, 2017; Pompili et al., 2019). The ratio between the value added of destination and that of country of origin (at constant prices) is included in the model to capture the effect of the level of development of each destination relative to each origin. When potential tourist is considering where to go, the weather is clearly a factor in his choice. This is supported by literature on the effects of climate on tourism demand (see among others Goh, 2012; Rosselló-Nadal, 2014; Li et al., 2017), and by the two recent studies by De la Mata and Llano-Verduras (2012) and Alvarez-Diaz et al. (2020), who find a positive effect of temperature and a negative influence of rainfall. In our study, we include the average, maximum, and minimum temperature, and annual level of precipitations in each destination for every year as a proxy of weather conditions. We collected data on weather conditions mainly from the Italian Institute for Environmental Protection and Research (ISPRA). We integrated data from this source with data from regional sources, such as the Regional Agency for Environmental Protection (ARPA) for the regions of Lombardy, Piedmont, Liguria, and Emilia-Romagna, and the Regional Hydrological and Geological Service (SIR) for Tuscany and Umbria. Finally, we consider the number of bank branches and the demand of public transport per capita as explanatory variables related to supporting services for tourism (see e.g. Crouch and Ritchie, 1999; Sánchez and López, 2015). Data are provided by ISTAT and can be freely accessed from the Statistical Territorial Atlas of Infrastructures.[9] Table 3.1 lists details on the definition of variables and data sources.

[8]Data on geographical distance were collected from the following website: www.distanza.org

[9]Data are accessible at the following web-page: `asti.istat.it/asti`. Since the variable number of bank branches has the same problem of comparability of data over time, we imputed data as described above for the dependent variable.

Table 3.1: Variables description and data source [a]

Variable	Definition	Source
ns	Logarithm of Nights spent/100 inhabitants in each destination from each country of origin	ISTAT
p	Logarithm of relative price of destination to origin (ratio between CPI of destination and CPI of origin)	ISTAT, OECD
v	Logarithm of relative value added at constant price (ratio between VA of destination and VA of origin)	EUROSTAT
D	Geographical distance (km) between the centroid of country of origin and the centroid of destination	www.distanza.org
T	Yearly maximum temperature of destination	ARPA, ISPRA *ambiente*, *Servizio Idrologico e geologico Regionale* (SIR)
Tm	Yearly minimum temperature of destination	ARPA, ISPRA *ambiente*, *Servizio Idrologico e geologico Regionale* (SIR)
Pre	Yearly level of precipitations of destination	ARPA, ISPRA *ambiente*, *Servizio Idrologico e geologico Regionale* (SIR)
Bank	Yearly number of bank branches of each destination	ISTAT (from the Statistical Territorial Atlas of Infrastructures). asti.istat.it/asti
Transp	Yearly number of tickets per inhabitants for public transport of each destination	ISTAT (from the Statistical Territorial Atlas of Infrastructures). asti.istat.it/asti

[a] ISTAT: Italian Institute of Statistics; OECD: Organisation for Economic Cooperation and Development; EUROSTAT: European Statistical Office; ARPA: *Agenzia Regionale per la Protezione Ambientale*; ISPRA: *Istituto Superiore per la Protezione e la Ricerca Ambientale*.

3.3.2 Patterns and trends in the data

This section describes the temporal and spatial patterns of the variables included in the proposed gravity model for spatial panel data of Italian inbound tourism demand. Figure 3.1 shows the logarithm of nights spent per 100 inhabitants by international tourists in Italian tourist establishments. As the graph illustrates, inbound tourism demand in Italy, from the 23 countries of origin used in this study, after a first year of decline, started to grow rapidly over the period 2004-2007. In 2008 tourism flows stopped growing and in 2009 inbound tourism demand in Italy began decreasing. This was undoubtedly due to the crushing effects of the Great recession. The crisis started at the end of 2007 in the USA and rapidly hit the European economy. It was the deepest recession since the Great depression in the 1930s, with severe effects on GDP and employment. Indeed, between the second quarter of 2008 and the second quarter of 2009, the GDP of the European Union (EU27) recorded a fall of 4.9%, and employment decreased by 1.9%; in Italy, these two indicators decreased by 6% and 0.9% respectively (EUROSTAT, 2009). According to EUROSTAT (2010), the number of nights spent by non-residents in tourist accommodations of EU27 experienced a decrease of 7.7% (0.8% for residents) in 2009 compared with 2008. In 2010, inbound nights spent in Italy started to rise again until 2013; in 2014, there was a slight decrease, but after this year inbound tourism demand in Italy recorded sustained growth until 2017, the last year in our sample.

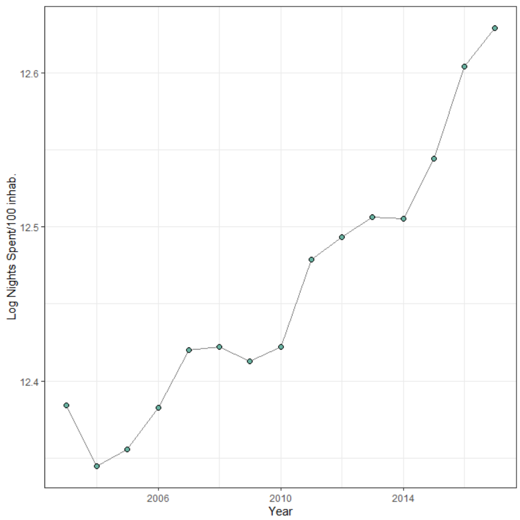
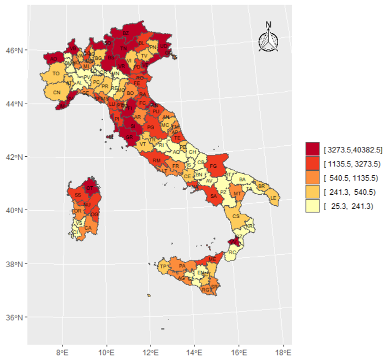
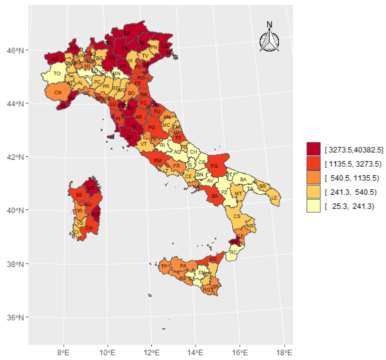


Figure 3.1: Nights spent per 100 inhabitants (Log), 2003-2017.

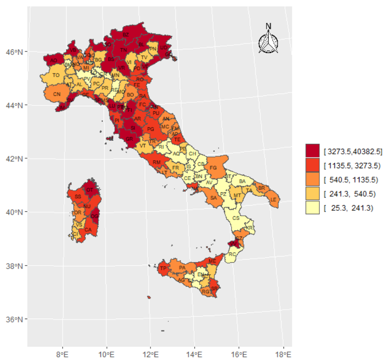
Figure 3.2 shows, based on quintiles of the pooled dataset, the spatial distribution of inbound tourism demand among Italian tourist destinations (NUTS3 regions) in four selected years (2004, 2009, 2013, 2017). The maps show that inbound tourism demand in Italy has followed the traditional North-South divide. Indeed, destinations in the northern part of Italy are the most attractive with a significant number of destinations in the right tail of the distribution (darker colours), while most of destinations in the South have tourist flows lower than the median (lighter colours). Two exceptions to this are the two main Italian islands (i.e. Sicily and Sardinia) where a notable number of destinations fall in the right tail of the distribution. The North-South division is stable over time and the geographical distribution of tourist flows is almost constant over time too. An interesting phenomenon to be noted is the presence of local clusters with similar levels of tourist flows. For example, two clusters with dark colours appear in the North of Italy; one in the North-East around *Trento* and *Bolzano*, and the second in the neighbourhood of *Siena* and *Firenze*.



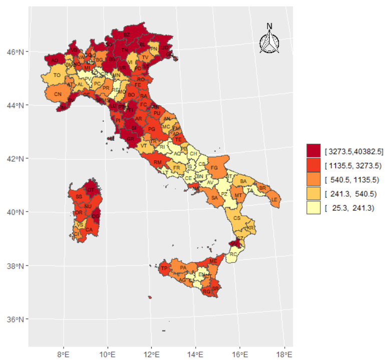
(a) 2004



(b) 2009



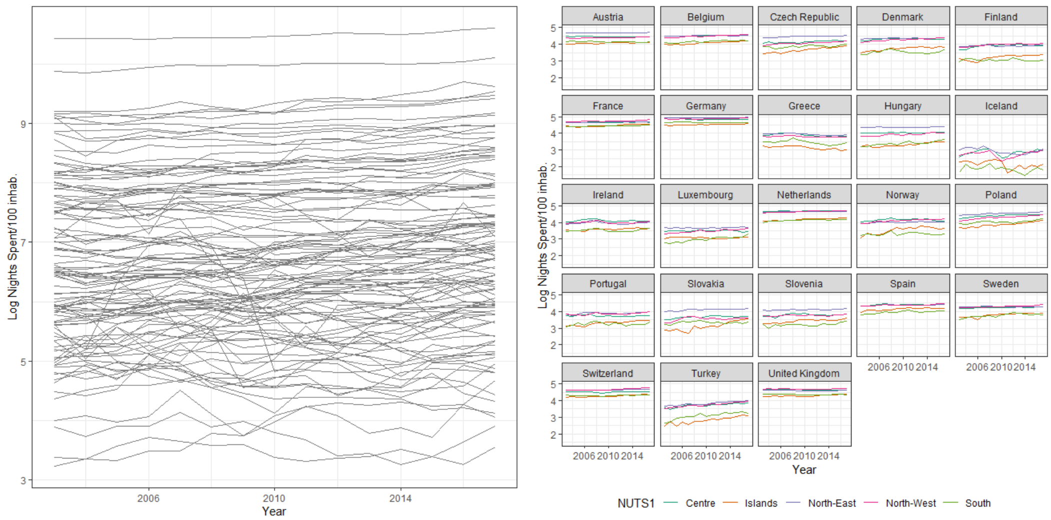
(c) 2013



(d) 2017

Figure 3.2: Nights spent per 100 inhabitants (Log), selected years. Class intervals based on quintiles of the entire distribution of the pooled data (all destinations, all origins, all years).

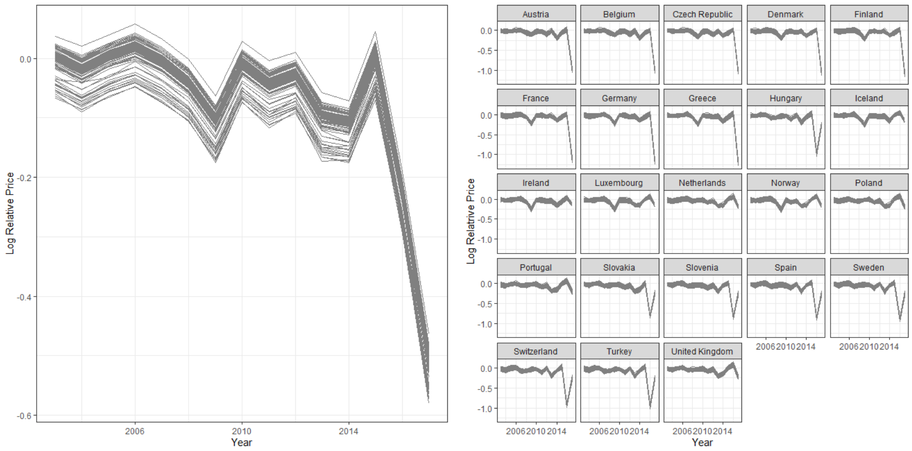
Figure 3.3 plots the temporal evolution of inbound tourist flows of all the 110 Italian provinces in panel (a), and NUTS1 trend for the 23 countries of origin in the sample in panel (b). From panel (a) it can be seen that inbound tourist flows differ across provinces and that in most regions the trend is upward. In panel (b) where patterns of data for the 23 countries of origin can be seen, it emerges that inbound tourist flows vary with countries of origin in both magnitude and patterns. For example, France and Germany seem to be the most important markets for Italian inbound tourism demand. Iceland is among the countries that generate few tourist flows, and patterns in the North of Italy differ from those in the South (i.e. increasing in the North, and decreasing in the South).



(a) (b)

Figure 3.3: Nights spent (log) provincial trends on the left (a), and NUTS1 trends for the 23 origins on the right (b)

Looking at the explanatory variables, Figure 3.4 shows the evolution over time of the logarithm of relative price, averaged over countries of origin, for the 110 regions on the left (panel a), and for each origin-destination pair on the right. Panel (a) indicates that relative price in the various regions follows almost the same pattern, but with some differences among regions. Panel (b) enables us to evaluate differences among origins where each subpanel plots the relative price of the 110 destinations for a fixed origin, i.e. the CPI of destination (the numerator in the variable price) changes, while the CPI of origin (the denominator of the variable price) is fixed. Therefore, looking at each individual subpanel we can assess differences among prices of destinations, whereas comparing subpanels one with another, differences of cost of living across countries of origin can be assessed. It emerges that price differs among destinations regardless of the origin, as shown in panel (a), and that the variable price shows almost the same pattern in all the countries of origin, although in France, Germany, Greece, Ireland, and Luxembourg the decline of price during the crisis is more pronounced than in other countries.

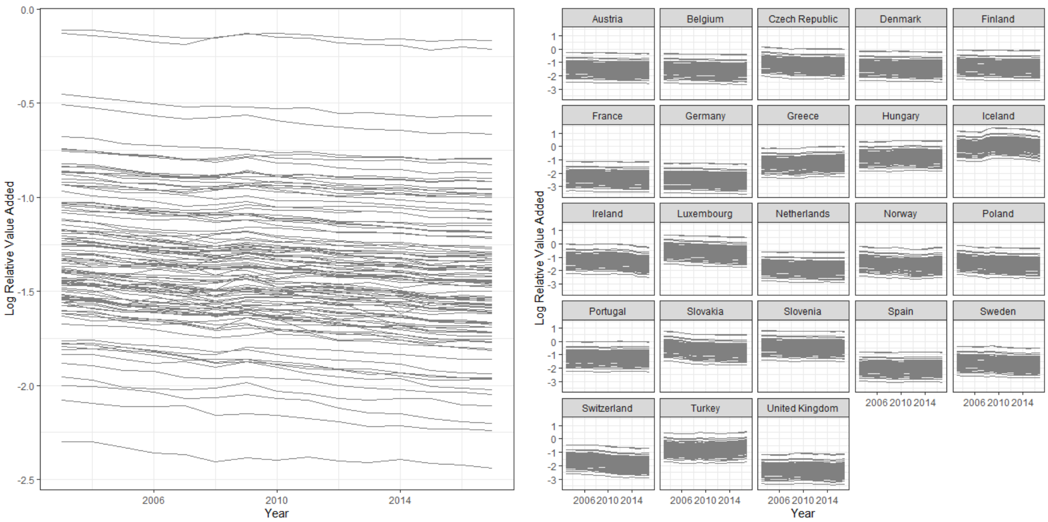


(a) destination pattern (b) origin-destination pattern

Figure 3.4: Log of relative price

Figure 3.5 reports similar plots for the variable value added. On the left, we find the graph of value added, averaged over origins, for the 110 destinations. It can be seen that there is a negative trend in the relative value added averaged over origins which varies highly across regions. Panel (b) gives a more detailed picture of this variable, as it shows the value added for each origin-destination pair. Looking at each sub panel, where the value added of origin is fixed, the variability of value added across destinations is confirmed. Comparing the subpanels one with another, we can identify the most developed countries as they are the ones with the higher value added. Since the value added of origin is the denominator of the variable, the countries with lower values of this variable are those with higher value added. Since the graphs in the subpanels show different levels, the value added of the selected countries is different, and France, Germany, and United Kingdom are those with the highest value added.

Figure 3.6 describes the weather conditions of the 110 destinations in the form of graphs. The annual maximum temperature of such destinations can be found in panel (a). This variable exhibits an increasing trend with some years of negative peaks (e.g. 2007, 2010, and 2013). It can be noted that the maximum temperatures tend to move together in most of destinations, but there are some differences like the group of regions with much lower temperatures than the mean group. Panel (b) of Figure 3.6 plots the minimum temperature (yearly average) of the 110 destinations. The minimum temperature is different across regions and is increasing. These differences in temperature are

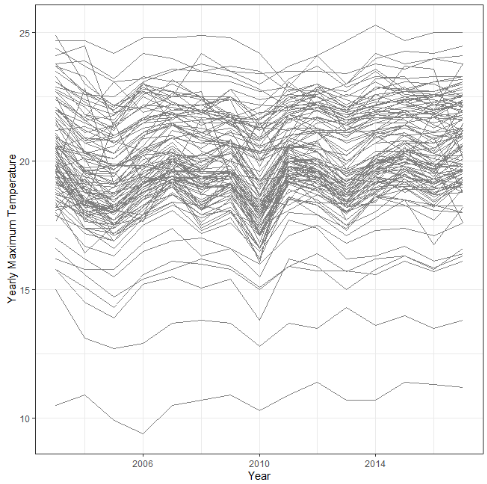


(a) destination pattern (b) origin-destination pattern

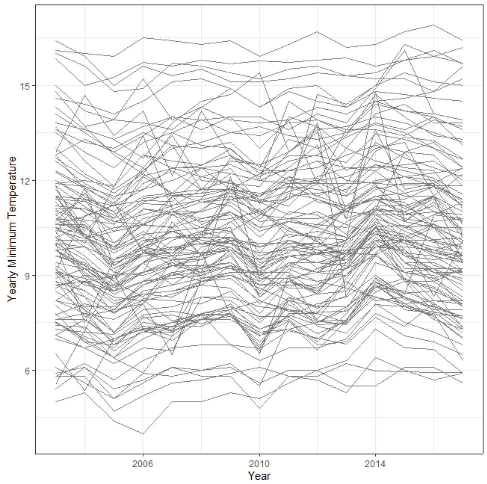
Figure 3.5: Log of relative Value Added (VA)

to be expected because Italy extends in a North-South direction, so weather conditions can be very different in the South compared to the North. Panel (c) in Figure 3.6 shows the yearly amount of precipitations (in mm). The graph shows a great deal of variation over time and across destinations with peaks in 2004, 2008, 2010, and 2014.

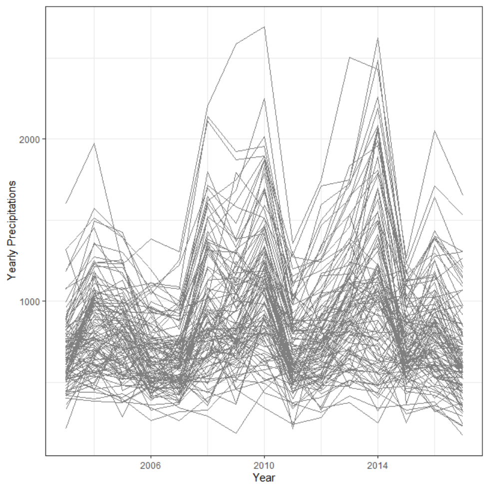
Finally, Figure 3.7 shows the temporal evolution of the number of bank branches (panel a) and per capita demand for public transport (panel b) in all the 110 destinations. The number of bank branches rose until 2008 after which there was a continuous decline. This may be the effect both of the crisis and the increase of on-line banking over recent years. The demand for public transport varies among destinations, with four destinations having a much higher level of public transport demand than the others. However there is no uniform pattern, as some destinations have an increasing demand for transport, while in others the trend is negative.



(a) yearly maximum temperature

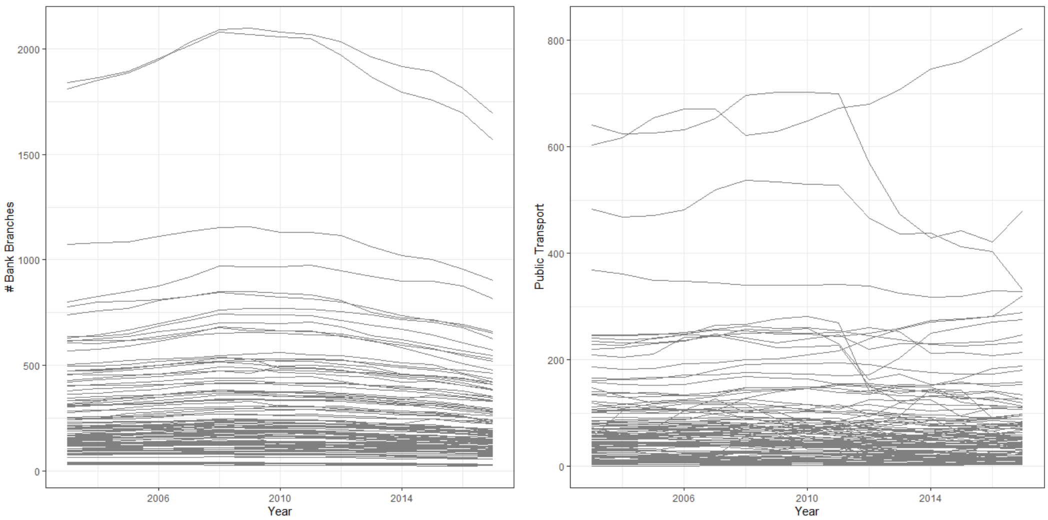


(b) yearly minimum temperature



(c) yearly amount of precipitations

Figure 3.6: Weather conditions of Italian provinces (NUTS3 regions)



(a) number of bank branches (b) per capita demand for public transport

Figure 3.7: Bank branches (no the left) and demand for public transport (on the right), destination trends.

3.3.3 Modelling strategy

To explore the inbound Italian tourism demand, the following dynamic spatial panel data model with common factors and gravity structure for tourism demand has been proposed:

$$\begin{aligned} ns_{ijt} = \tau ns_{ijt-1} + \rho W ns_{ijt} + \eta W ns_{ijt-1} + \beta_1 p_{ijt} + \beta_2 v_{ijt} + \\ \beta_3 D_{ij} + \beta_4 T_{it} + \beta_5 Tm_{it} + \beta_6 Pre_{it} + \beta_7 Bank_{it} + \beta_8 Transp_{it} + \\ WX\boldsymbol{\theta} + \boldsymbol{\Gamma_1} \overline{ns}_{jt} + \boldsymbol{\Gamma_2} \overline{ns}_{jt-1} + \mu_i + \mu_j + \varepsilon_{ijt} \end{aligned} \tag{3.1}$$

where ns_{ijt} is the logarithm of the nights spent in destination i ($i = 1, \ldots, 110$) from origin j ($j = 1, \ldots, 23$) at time t ($t = 2004, \ldots, 2017$), which is the dependent variable.[10] ns_{ijt-1} is the time lag of the dependent variable, and Wns_{ijt} and Wns_{ijt-1} are the spatial lag and the spatial-temporal lag of the dependent variable, respectively. p_{ijt} is the logarithm of the relative price of destination i with respect to origin j at time t. It is computed as the ratio between the Consumer Price Index (CPI) of destination i at time t and the CPI of origin j at time t. v_{ijt} is the logarithm of the relative value added at constant prices of destination i with respect to origin j at time t. It is computed as the ratio

[10] In tourism demand literature the log specification seems to be widely used (see among others, Lim and Zhu, 2017; Tang and Tan, 2016; Kusni et al., 2013; Garín Muñoz, 2007; Maloney and Montes Rojas, 2005). The success of this model specification is mostly due to the fact that coefficients can be interpreted as elasticities.

between the Value Added (VA) at constant prices of destination i at time t and the VA at constant prices of origin j at time t. D_{ij} is the distance in kilometres between origin and destination. T_{it} and Tm_{it} are yearly maximum and minimum temperatures respectively of each destination at time t. We excluded average temperatures from the analysis due to collinearity concerns. Pre_{it} is the yearly amount of precipitations (i.e. rain, snow, and hail) in destination i at time t. These three variables are proxies of weather conditions in destination i at time t. The variable $Bank_{it}$ is the number of bank branches of each destination at time t, and $Transp_{it}$ is the number of tickets for public transport purchased per inhabitant. WX represents the spatial lag of the aforementioned covariates. W is the 110×110 spatial weight matrix that describes the spatial relationship among spatial units. To select the optimal W matrix, we compared different W matrices specifications with each other ceteris paribus and repeated this procedure for different model specifications.[11] The specification and selection of this matrix will be further discussed in the discussion of the results.

The common factors are defined as the cross-sectional averages of the dependent variable at time t and $t-1$, i.e. $\overline{ns}_{jt} = I^{-1}\sum_{i=1}^{I} ns_{ijt}$ and $\overline{ns}_{jt-1} = I^{-1}\sum_{i=1}^{I} ns_{ijt-1}$.[12] Their scope is to capture potential strong cross-sectional dependence in the dependent variable. Additional common factors could be added by means of cross-sectional averages of covariates. However, each common factor included in the model has an estimate of I additional parameters.

The first attempt to account for observed and unobserved common factors is that of Pesaran (2006). Subsequently, Pesaran et al. (2013) defined common factors in a dynamic but non-spatial framework. Bailey et al. (2016a) made a step forward proposing a two-step method to account for both weak and strong cross-sectional dependence in a dynamic and spatial framework. Recently, Halleck Vega and Elhorst (2016) show that if one controls for both weak and strong cross-sectional dependence, it is necessary to include cross-sectional averages of the dependent variable at time t and $t-1$. Based on the assumption of Pesaran (2006), that the weight of each spatial unit in the cross-sectional average tends to zero when the cross-sectional dimension diverges, common factors can be treated as exogenous covariates.

Since we have 110 spatial units (i.e. the 110 Italian NUTS3 regions), the weight of each cross-sectional unit is quite small, and hence this assumption is more likely to be met than in Ciccarelli and Elhorst (2018) and Halleck Vega and Elhorst (2016), whose studies are based rispectively on 69 and 12 spatial units only. The model also includes destination and origin fixed effects, termed μ_i and μ_j, respectively. Destination fixed effects capture all destination-specific characteristics that are fixed over time, whereas origin fixed effects catch those of countries of origin. Since the model is defined in

[11] Within the literature on spatial modelling of tourism demand, the most popular spatial weight matrices (W) are the row-normalised binary contiguity matrix and the k-nearest neighbours.

[12] Where I is the number of destinations, 110 in our case.

an origin-destination framework, the inclusion of these two fixed effects is important because they are proxies of origin and destination size. ε_{ijt} is the i.i.d. error term with zero mean and finite variance σ^2. The model is estimated by the bias-corrected Quasi Maximum Likelihood estimator proposed by Yu et al. (2008). Since parameter estimates of the model in Equation 3.1 are not directly interpretable, Elhorst (2014) suggests that direct and indirect effects of covariates be evaluated. They can be computed from the matrix of partial derivatives of the expected value of the dependent variable with respect to the $k-th$ explanatory variable, which in the long term reads as

$$\begin{aligned}\left(\frac{\partial E(ns_t)}{\partial(x_{1k})}\cdots\frac{\partial E(ns_t)}{\partial(x_{Nk})}\right) &= \begin{pmatrix} \frac{\partial E(ns_{1t})}{\partial(x_{1k})} & \cdots & \frac{\partial E(ns_{1t})}{\partial(x_{Nk})} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(ns_{Nt})}{\partial(x_{1k})} & \cdots & \frac{\partial E(ns_{Nt})}{\partial(x_{Nk})} \end{pmatrix} \\ &= ((1-\tau)I_N-(\rho+\eta)W)^{-1}\begin{pmatrix} \beta_k & \theta w_{12} & \dots & \theta w_{1N} \\ \theta_k w_{21} & \beta_k & \dots & \theta w_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_k w_{N1} & \theta_k w_{N2} & \dots & \beta_k \end{pmatrix}\end{aligned} \tag{3.2}$$

The average of diagonal elements represents the average direct effect, while the average of the row sum of off-diagonal elements is the average indirect effect (or the spillover effect). The former represents the impact (in the long run) of a change in the $k-th$ explanatory variable on the dependent variable in the same spatial unit. The second, the spillover effect, is a measure of the long-term effect of a change in the $k-th$ explanatory variable in neighbouring regions on the dependent variable of a spatial unit. Standard errors, and therefore the significance of these effects, are computed with the bootstrap procedure. The short-term version of direct and indirect effects is computed by imposing that $\tau=\eta=0$ (Elhorst, 2014).

Another important aspect to explore is whether the model is stable, explosive or if there is spatial cointegration in the dependent variable. Indeed, parameter estimates of dynamic spatial panel data models are consistent only if the stability condition holds (Yu et al., 2008). The stability of the proposed model will be tested with the method proposed by Lee and Yu (2010) and Yu et al. (2012). This method looks at the sum of the parameter estimates of the lagged dependent variable in time (τ), space (ρ), and both time and space (η). More precisely, the model is stable if the sum of these three coefficients is less than one ($\tau+\rho+\eta<1$), and it is explosive when this sum is greater than one ($\tau+\rho+\eta>1$). Finally, if the sum of the three coefficients is equal to one, the dependent variable is spatially cointegrated. When the stability condition does not hold, the quasi-maximum likelihood estimator of Yu et al. (2008) needs adjustments to get a consistent estimator.

As far as the gravity framework is concerned, the introduction of spatial and temporal dependence consists of augmenting the linear gravity equation by means of spatially and temporally lagged variables (both dependent and independent). To achieve this, Marrocu and Paci (2013), following Le Sage and Pace (2008, 2009) augmented the linear gravity model with three additional spatial autoregressive components, accounting for origin, destination and origin-destination dependence. Other studies considered a simple spatial autoregressive model including the spatial lag of the dependent variable only for destination (De la Mata and Llano-Verduras, 2012; Alvarez-Diaz et al., 2017), while Pompili et al. (2019) estimated a spatial Durbin model. As mentioned previously, up to now few studies have employed spatial panel models in the gravity framework for analysing tourism demand (Deng and Athanasopoulos, 2011; Patuelli et al., 2013, 2014). Among them, only Deng and Athanasopoulos (2011) estimate a dynamic spatial autoregressive model, whereas Patuelli et al. (2013, 2014) estimate a static spatial panel model but include spatial effects of covariates.

To the best of our knowledge, our study is the first attempt at applying a dynamic spatial panel data model with common factors in the origin-destination framework to study tourism demand.

3.4 Results

The first step of our analysis is to test the presence of cross-sectional dependence in the dependent variable. To accomplish this, we compute the CD test proposed by Pesaran (2015), whose null hypothesis is no presence of cross-sectional dependence. We obtained a CD test value (for row data) of 99.146, which is outside the interval (-1.96, 1.96), therefore, we have evidence against the null hypothesis of no cross-sectional dependence at the 5% significance level. To assess whether the cross-sectional dependence is strong, we use the exponent α-test of Bailey et al. (2016b). The result of this test for the dependent variable is $\alpha = 1.0007$ with a standard error of 0.0302, suggesting the presence of strong cross-sectional dependence. This result clearly shows the need to control for strong cross-sectional dependence including common factors in the model.

Next we followed a procedure to select an appropriate model, at first estimating a dynamic spatial panel data model with spatial (origin and destination) and time fixed effects, but without common factors. At this stage, we considered a row-normalized binary contiguity matrix. The CD-test on the residuals of this model takes the value -11.137, indicating the presence of cross-sectional dependence. Nevertheless, this value is much lower than the CD-test value on raw data which means that the DSPD with time and spatial fixed effects captures most of the cross-sectional dependence in the dependent variable. In the light of these results, we estimate a DSPD model including common factors at time t and $t-1$ approached by cross-sectional averages of the dependent variable, and we use the same W row-normalized binary contiguity matrix, so that the model is able to capture the remaining cross-sectional dependence. The CD-test on residuals of this latter model takes the value -6.492, which is still outside the interval (-1.96, 1.96). However, this result could be due to the matrix we choose. Since the spatial weight matrix (W) is a key issue in spatial econometrics, because spatial spillovers are highly dependent on W, we have to be careful which one we choose. Hence, keeping the model specification fixed, we compare the results from various DSPD model specifications with different W matrix specifications in order to select the W matrix with the best performance. This is done through the Log-likelihood value (higher values are better) and the CD-test on residuals of the model (test results in or closer to the confidence interval (-1.96, 1.96) are better).

The following W matrices were considered: row-normalized first and second order binary contiguity matrices, inverse distance matrices (row-normalized both by row and by the largest eigenvalue), and inverse distance to the power of 3 (where the generic element is $w_{ij} = 1/d_{ij}^3$). We also considered k-nearest neighbours contiguity type W matrices for k=5,...,17 (row-normalized). The start and end values of k are based on the average number of neighbours of the first and second order binary contiguity matrices, because the best choice seems to be somewhere between the first and second order row-normalized binary contiguity matrix, based on log-likelihood values.

For the sake of brevity, here we will only discuss the results of the W matrix selection for the model specification shown in equation 3.1 regarding the specification with (DSPD-WCF) or without common factors. The log-likelihood value of the model with common factors is higher than the model without them for all the W matrices specifications, hence the model with common factors is preferred. Since the CD-test of the DSPD-WCF is outside the interval (-1.96, 1.96) for all the W matrices considered, the choice of the optimal W matrix is based on comparing the log-likelihood values for the different W matrices. Among k-nearest neighbours W matrices, the matrices with six and eight neighbours give the two highest log-likelihood values (58452.25 and 58453.03, respectively). The log-likelihood with the binary contiguity matrix is 58481.66, which is the highest one. Nevertheless, we choose the k-nearest neighbours matrix with $k=6$ because of the presence of islands among the spatial units.

Table 3.2 shows estimation results for three different specifications of the proposed model. The first column reports the results of the model with origin and destination fixed effects (μ_j and μ_i) and time fixed effects but, without common factors. The CD-test on the residuals of this model gives evidence of residual cross-sectional dependence. The second column shows results of the model as in Equation 3.1, i.e. including spatial fixed effect and common factors approached by cross-sectional averages. The CD-test on the residuals of this model is significant at 5%, indicating that the model is not able to capture all the cross-sectional dependence in the data. Since the model with common factors achieves better results in terms of Log-likelihood (58452.25 vs. 45483.83), we can say that it outperforms the model without common factors. As stated in the methodological section, the dynamic spatial panel data model is stable only if the stability condition $\tau+\rho+\eta<1$ is fulfilled. In both models this condition is not satisfied, indeed the sum of serial, spatial, and spatiotemporal coefficients is close to one (1.014 for the preferred model). Therefore, we re-estimate the model with common factors (DSPD-WCF) with the constraint $\tau+\rho+\eta=1$; these results are reported in the third column of Table 3.2.

Table 3.2: Estimation results

Covariates	**DSPD** [a]		
	Sfe+Tfe [b]	Sfe+CSA[b]	Sfe+CSA restricted[d]
ns_{t-1}	0.988099	0.986057	0.985100
	(876.863281)	(890.88)	(896.48)
Wns_t	0.215208	0.164857	0.167438
	(22.890010)	(18.86)	(19.17)
Wns_{t-1}	-0.185494	-0.136777	-0.152537
	(-19.038356)	(-15.12)	(-17.38)
p	-0.048379	-0.040936	-0.041404
	(-0.975369)	(-0.84)	(-0.85)
v	0.023735	0.051040	0.050857
	(1.092214)	(2.13)	(2.13)
D	1.66E-09	-1.32E-07	-4.52E-07
	(0.001349)	(-0.11)	(-0.37)
T	0.001653	0.001650	0.001668
	(2.186452)	(2.09)	(2.11)
Tm	-0.000374	0.000036	0.000020
	(-0.548974)	(0.05)	(0.03)
Pre	-0.000005	-0.000004	-0.000004
	(-2.069038)	(-1.53)	(-1.54)
$Bank$	-0.000078	-0.000089	-0.000089
	(-4.562952)	(-4.88)	(-4.84)
$Transp$	0.000063	0.000055	0.000056
	(2.971869)	(2.35)	(2.37)
$W \times p$	-0.061156	-0.032311	-0.034864
	(-0.622555)	(-0.33)	(-0.36)
$W \times v$	-0.023930	0.001719	0.002125
	(-0.605089)	(0.04)	(0.05)

(Continued on next page)

Table 3.2 *(continued)*

Covariates	**DSPD** [a]		
	Sfe+Tfe [b]	Sfe+CSA[b]	Sfe+CSA restricted[d]
$W \times D$	0.000001	0.000001	-0.000002
	(0.625925)	(0.30)	(-0.77)
$W \times T$	-0.005464	-0.003454	-0.003333
	(-3.588432)	(-2.21)	(-2.13)
$W \times Tm$	-0.001353	-0.001970	-0.002119
	(-0.871498)	(-1.22)	(-1.32)
$W \times Pre$	-0.000002	-3.71E-07	-2.37E-07
	(-0.390034)	(-0.09)	(-0.06)
$W \times Bank$	-0.000082	-0.000086	-0.000081
	(-2.339144)	(-2.40)	(-2.26)
$W \times Transp$	0.000055	0.000078	0.000078
	(1.301785)	(1.64)	(1.64)
Log-lik	45483.83	58452.25	
R^2	0.9804	0.9654	
CD-test (residuals)	-10.611	-6.702	
$\hat{\tau}+\hat{\rho}+\hat{\eta}$	1.0178	1.0141	
CD-test (row data)	99.146		

[a] t-values in parenthesis. Bias-corrected ML estimates (Yu et al., 2008) with k-nearest neighbours matrix (k=6). Origin and destination fixed effects and common factors have not been reported for the sake of space.
[b] Sfe+Tfe: DSPD model with spatial (origin and destination) and time fixed effects.
[c] Sfe+CSA: DSPD model with spatial fixed effects and common factors approached by Cross-Sectional Averages (CSA).
[d] Based on the model with restriction $\tau+\rho+\eta=1$

When this latter transformation is applied, the spatial multiplier matrix in the long-term become singular, and therefore, long-term direct and indirect effects are not defined. We can only compute short-term effects.

Looking at the estimations in column three of Table 3.2, some interesting results can be highlighted. Firstly, the serial autoregressive coefficient is positive and significant, indicating the presence of positive temporal dependence in Italian inbound tourism demand, and hence, a positive habit effect. This finding is in line with results of the study of Massidda and Etzo (2012) for Italian domestic tourism demand and the recent study of Deng and Athanasopoulos (2011) for Australian domestic and international tourism demand. There are two possible explanations for this result. First, tourists are more likely to return when they have enjoyed their stay; second, when tourists return home, they talk positively about their holiday to people in their social network such as friends,

parents, relatives, and colleagues which leads to a diffusion effect. In other words, this result gives insights into why Italian tourist destinations are so highly popular in the international market.
A second explanation for this result is that the estimations show the presence of spatial and spatiotemporal dependence in international tourism demand for Italian destinations. The spatial autoregressive coefficient is positive and significant; this coefficient captures the effect of a change in tourism demand in neighbouring destinations on tourism demand in a destination. The sign of this coefficient is consistent with the recent study on international tourism demand in Italy by Pompili et al. (2019). Similar results have also been found in the case of Italian domestic tourism flows (see among others Marrocu and Paci, 2013). This means that the presence of well-performing destinations in the neighbourhood leads to a positive effect on the tourism demand of a destination. This result gives insights about the positive effect that cooperation among tourist destinations could have on the attractiveness of a destination with perhaps, an improvement in their profitability. On the other hand, the spatiotemporal autoregressive coefficient is significant and negative, and hence, the empirical regularity $\eta = -\tau * \rho$ is satisfied. Imposing this constraint on parameters of the model could remove overidentification problems (Parent and Le Sage, 2012, 2011). Elhorst (2010) shows that if empirical regularity is satisfied, space and time effects can be separated mathematically, thus simplifying the interpretation of results. From an empirical perspective, the spatiotemporal coefficient (η) can be interpreted as the word of mouth effect (Liu, 2020). The fact that the sign of this coefficient is negative, therefore suggests that Italian inbound tourism demand has in some way lost some of its attractiveness. This might be connected with the role of curiosity in the choice of the destination. Curiosity is one of the most important driving factors of destination choice (Martenson, 2018). According to Litman (2005), curiosity involves an interplay between desire (for new information) and expected pleasure. Visitors to neighbouring regions could decrease the desire of potential tourists to collect information on the destination, and hence their curiosity and likelihood that they will visit it and talk about their stay. This mostly affects new visitors to a destination, because as noted by Jacobsen and Munar (2012), new tourists are more likely to collect information from external sources than repeat visitors.

These results have two main policy implications. The first concerns the importance of cooperation among Destination Management Organisations (DMOs) of different destinations to improve their attractiveness by extending the variety of tourist products on offer. This cooperation strategy might increase the habit effect, in addition to reducing the negative word of mouth effect; indeed, a greater variety of tourist attractions might lead to an increase of repeat tourists. The second policy implication is about the need of less well-known destinations to invest in the renewal of their product and in strengthening their image so as to improve their attractiveness.

Table 3.3 reports the short-term direct and spillover effects that capture the effect on tourism demand in one destination due to a change in its own and its neighbours' covariates.

Table 3.3: Short-term direct and spillover effects [a]

	Direct	Spillover	Total
p	-0.037457	-3.12E-06	-0.037460
	(-0.72)	(-0.59)	(-0.72)
v	0.051081	0.001645	0.052726
	(2.08)	(2.10)	(2.14)
D	-2.37E-07	2.14E-05	2.12E-05
	(-0.19)	(0.03)	(0.03)
T	0.001641	-3.88E-06	0.001637
	(2.10)	(-1.58)	(2.09)
Tm	2.14E-05	-8.75E-05	-0.000066
	(0.03)	(-4.67)	(-0.10)
Pre	-4.01E-06	5.39E-05	0.000050
	(-1.64)	(2.19)	(2.01)
Bank	-8.78E-05	-0.037956	-0.038044
	(-4.67)	(-0.40)	(-0.40)
Transp	5.38E-05	-0.000728	-0.000674
	(2.19)	(-0.02)	(-0.02)

[a] t-values in parenthesis. Based on the model with restriction $\tau+\rho+\eta=1$

As expected, the sign of direct and indirect effect of relative price (p) is negative, but neither direct nor indirect effects are significant. As concerns the value added variable, we find significant positive values for both direct and indirect effects. This result suggests that the level of development of a destination has a positive impact on tourism demand, probably because more developed destinations can offer higher quality services.

The short-term effects of this variable read as elasticities, since value added enters the model in logarithm. The positive sign of the total effect of this latter variable indicates that a 1% increase in the level of development of the destination will produce an increase of 0.0527% in tourist flows. Most of this contribution is ascribable to the direct effect, suggesting that the value added of a destination plays a major role. Nevertheless, the positive sign of the indirect effect of value added indicates that the level of development of neighbouring regions does have a positive effect on tourism demand of a destination.

Total and direct effects of maximum temperature are positive and significant, whereas

the indirect effect is negative but not significant. Therefore, an increase in the maximum temperature will have positive effects on tourism demand. A significant spillover effect emerged for minimum temperature, but its magnitude is very low. Hence, an increase in the minimum temperature in neighbouring destinations leads to a negative but minimal effect on tourism demand in a destination. Total and direct effects of minimum temperature are also negative but not significant. These results indicate that the presence of warmer destinations in the neighbourhood of one destination reduces the desire of tourists to go there, and that warmer destinations are preferred.
The total effect of the level of precipitations is positive and significant, but very low. The positive sign of this effect seems surprising if we neglect the decomposition of the total effect into direct and indirect effects. As regards the latter, we find that the positive sign of the total effect is due to the positive sign of the spillover effect, which is much higher than the direct one. The positive sign of the spillover effect of precipitations is in line with expectations, because if a destination is surrounded by neighbours with higher levels of precipitations, tourists will choose that destination. The direct effect of precipitations is negative as expected, but is not significant.

The limited importance of weather in explaining tourism demand may be due to the fact that Italy is a Mediterranean region where the weather is good almost year round and even more so in recent years due to the effects of global warming. So, it is a plausible hypothesis that the weather is not a key factor as international tourists perceive Italy as a warm destination as a whole.
As far as variables related to auxiliary services for tourism are concerned, we find that only the direct effect of the number of bank branches is negative and significant, but is almost equal to zero. Although the low magnitude of the coefficient, its negative sign might give insights of a no well developed regional financial system. That is, a high number of bank branches in a destination might signify that some services such as electronic means of payment and the possibility for cash withdrawals at ATMs are limited. That might be a constraint to tourism development. The effects (direct, spillover, and total) of public transport per capita are not significant and are close to zero. This result might be surprising, although not in the case of international tourism demand because international tourists usually buy holiday packages from travel agents which almost always include transportation services operated by private companies. Therefore, it seems that the level of public transport is not an important determinant of international tourism demand.

3.5 Concluding Remarks

The chapter has explored the main determinants of inbound tourism demand in the 110 Italian provinces (NUTS3 regions) from 23 countries of origin taking into account the spatial dimension of the phenomenon. In particular, the chapter has investigated spatial effects in tourism demand by applying a dynamic spatial Durbin panel data model with common factors within the origin-destination framework, including the spatial lag of explanatory variables as suggested by Halleck Vega and Elhorst (2015). In doing so, we address a gap in the literature, where current spatial studies in the origin-destination framework neglect the presence of weak/strong cross-section dependence. Although there are a few studies using spatial econometric models in the origin-destination framework in the literature, most of them focus on a single time period, and comparatively little research have been done within the spatial panel data setting (see e.g. Deng and Athanasopoulos, 2011; Patuelli et al., 2013, 2014). Nevertheless, even these studies neglect some important aspects of spatial dependence. For example, Deng and Athanasopoulos (2011) account for habit formation effects by using a dynamic SAR, but neglect exogenous spillover effects (WX) and possible strong cross-sectional dependence. This is in part addressed by Patuelli et al. (2013, 2014), by means of the inclusion of WX, but they only consider a static model. Therefore, to the best of our knowledge, our study is the first attempting to fill this gap in the literature by proposing the application of a model that simultaneously accounts for time-dependency, and the spatial and spatiotemporal features of tourism demand, along with the presence of strong cross-sectional dependence. It is for this reason that we use a dynamic spatial Durbin model with common factors in the origin-destination framework. This is a model which makes a significant contribution since it enables a better interpretation of spatial spillover effects to made and reduces the problem of omitted variables noted by Corrado and Fingleton (2012) including the spatial lag of covariates. Furthermore, the model used in this study, controlling for the presence of strong cross-section dependence and the presence of spatial cointegration, reduces misleading inference. Finally, it also accounts for unobserved push and pull factors fixed over time with origin and destination fixed effects.

A panel model of $110 * 23 * 15$ observations was built considering the inbound nights spent in the 110 Italian provinces from 23 countries of origin for the period 2003-2017. We considered two variables as proxy of the interplay between origin and destination, those of relative price and relative value added. Furthermore, we included as covariates the weather conditions of destinations, the number of bank branches, per capita demand for public transport, and geographical distance.

Differently from the previously applied spatial gravity models, the use of a dynamic spatial Durbin model with common factors contributes to a better understanding of the complex spatial features of tourist flows and, indeed, we find evidence of both temporal and spatial dependence. To be precise, we find a significant and positive effect of past tourist flows on present ones, which point to the presence of habit formation. Furthermore, we find evidence of a positive and significant effect of tourist flows in neighbouring destinations and the presence of negative word of mouth effect (i.e. the negative sign of the coefficient of WY_{t-1}).

Another noticeable result is the presence of significant direct and spillover effects of some explanatory variables. More specifically, we find positive and significant direct and spillover effects of value added, indicating that the level of development of both a destination and its neighbouring regions positively affects inbound tourism demand for that destination. Since the level of development of a region can be seen as a proxy of the quality of services, this result suggests that increasing the quality of services may have positive effects on the attractiveness of destinations. We also found that the weather conditions of destinations and those in the neighbouring regions do have some effect on tourist flows, with warm destinations being preferred.

We believe that the empirical evidence that has emerged from this study have important policy implications for Italian inbound tourism demand. In this regard, our study provides practitioners and destination management organisations interesting elements of destination attractiveness to consider. On the one hand, the positive sign of the spatial autoregressive coefficient indicates that one destination benefits from the presence of attractive destinations in the neighbourhood. Therefore, cooperation among destinations and a joint promotional effort may improve the attractiveness and profitability of the entire territory. However, this requires that policy makers, supported by local tourism managers need to build integrated and coordinated policies to enhance the attractiveness of tourism in local areas. This implies effective coordination of policies at different administrative levels, and communication between tourism management bodies from different areas. For example, a suitable strategy to exploit benefits from neighbouring regions could be to build a network of destinations and promote integrated tourism packages. This may help lesser-known destinations to improve their attractiveness, and hence, the attractiveness of the entire territory. On the other hand, destination managers should also plan for the renewal of a destination (for example by building new attractions) to reduce the negative word of mouth effect. This involves an effort at local level to make each destination a unique and ongoing experience, which tourists want to repeat over time. Combining this with multi-destination packages, destination managers could offer a great variety of options to meet the needs of a wide range of tourists and increase the attractiveness and profitability of destinations.

At the same time, the presence of positive direct and spillover effects of the level of development of regions (approximated by relative value added) indicates that public institutions and destination management organizations need to improve the quality of public services, because of their positive effects on tourism demand. Moreover, the positive influence of the quality of public services, due to positive spillover effects, is spread to neighbouring regions and contributes to their attractiveness too.

Finally, policy makers and tourism managers should be aware of the growth potential of tourism, and its benefits to the economy and create policies for tourism that exploit the unique features of local areas. However, this effective and efficient management of tourism resources should always be aimed at making tourism a more sustainable source of economic growth.

Appendix 3.A: Destinations and countries of origin

Table 3.A.1: Italian destinations (NUTS3 regions)

NUTS1	NUTS2	NUTS3
North-West	Piemonte	Torino
North-West	Piemonte	Vercelli
North-West	Piemonte	Biella
North-West	Piemonte	Verbano-Cusio-Ossola
North-West	Piemonte	Novara
North-West	Piemonte	Cuneo
North-West	Piemonte	Asti
North-West	Piemonte	Alessandria
North-West	Valle d'Aosta	Aosta
North-West	Liguria	Imperia
North-West	Liguria	Savona
North-West	Liguria	Genova
North-West	Liguria	La Spezia
North-West	Lombardia	Varese
North-West	Lombardia	Como
North-West	Lombardia	Lecco
North-West	Lombardia	Sondrio
North-West	Lombardia	Milano
North-West	Lombardia	Monza-Brianza
North-West	Lombardia	Bergamo
North-West	Lombardia	Brescia
North-West	Lombardia	Pavia
North-West	Lombardia	Lodi
North-West	Lombardia	Cremona
North-West	Lombardia	Mantova

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Table 3.A.1 *(continued)*

NUTS1	NUTS2	NUTS3
North-East	Trentino Alto Adige	Bolzano
North-East	Trentino Alto Adige	Trento
North-East	Veneto	Verona
North-East	Veneto	Vicenza
North-East	Veneto	Belluno
North-East	Veneto	Treviso
North-East	Veneto	Venezia
North-East	Veneto	Padova
North-East	Veneto	Rovigo
North-East	Friuli Venezia Giulia	Pordenone
North-East	Friuli Venezia Giulia	Udine
North-East	Friuli Venezia Giulia	Gorizia
North-East	Friuli Venezia Giulia	Trieste
North-East	Emilia Romagna	Piacenza
North-East	Emilia Romagna	Parma
North-East	Emilia Romagna	Reggio nell'Emilia
North-East	Emilia Romagna	Modena
North-East	Emilia Romagna	Bologna
North-East	Emilia Romagna	Ferrara
North-East	Emilia Romagna	Ravenna
North-East	Emilia Romagna	Forlì-Cesena
North-East	Emilia Romagna	Rimini
Centre	Toscana	Massa-Carrara
Centre	Toscana	Lucca
Centre	Toscana	Pistoia
Centre	Toscana	Firenze
Centre	Toscana	Prato
Centre	Toscana	Livorno
Centre	Toscana	Pisa
Centre	Toscana	Arezzo
Centre	Toscana	Siena

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Table 3.A.1 *(continued)*

NUTS1	**NUTS2**	**NUTS3**
Centre	Toscana	Grosseto
Centre	Umbria	Perugia
Centre	Umbria	Terni
Centre	Marche	Pesaro-Urbino
Centre	Marche	Ancona
Centre	Marche	Macerata
Centre	Marche	Fermo
Centre	Marche	Ascoli Piceno
Centre	Lazio	Viterbo
Centre	Lazio	Rieti
Centre	Lazio	Roma
Centre	Lazio	Latina
Centre	Lazio	Frosinone
South	Abruzzo	L'Aquila
South	Abruzzo	Teramo
South	Abruzzo	Pescara
South	Abruzzo	Chieti
South	Molise	Isernia
South	Molise	Campobasso
South	Campania	Caserta
South	Campania	Benevento
South	Campania	Napoli
South	Campania	Avellino
South	Campania	Salerno
South	Puglia	Foggia
South	Puglia	Barletta-Andria-Trani
South	Puglia	Bari
South	Puglia	Taranto
South	Puglia	Brindisi
South	Puglia	Lecce
South	Basilicata	Potenza

(Continued on next page)

Table 3.A.1 *(continued)*

NUTS1	**NUTS2**	**NUTS3**
South	Basilicata	Matera
South	Calabria	Cosenza
South	Calabria	Crotone
South	Calabria	Catanzaro
South	Calabria	Vibo Valentia
South	Calabria	Reggio di Calabria
Islands	Sicilia	Trapani
Islands	Sicilia	Palermo
Islands	Sicilia	Messina
Islands	Sicilia	Agrigento
Islands	Sicilia	Caltanissetta
Islands	Sicilia	Enna
Islands	Sicilia	Catania
Islands	Sicilia	Ragusa
Islands	Sicilia	Siracusa
Islands	Sardegna	Olbia-Tempio
Islands	Sardegna	Sassari
Islands	Sardegna	Nuoro
Islands	Sardegna	Oristano
Islands	Sardegna	Ogliastra
Islands	Sardegna	Medio Campidano
Islands	Sardegna	Cagliari
Islands	Sardegna	Carbonia-Iglesias

Table 3.A.2: Countries of origin

Austria	Germany	Netherlands	Spain
Belgium	Greece	Norway	Sweden
Czech Republic	Hungary	Poland	Switzerland
Denmark	Iceland	Portugal	Turkey
Finland	Ireland	Slovakia	United Kingdom
France	Luxembourg	Slovenia	

Chapter 4

Exploring the determinants of tourist destinations' resilience

4.1 Introduction

There has been increasing attention in tourism literature on how tourism reacts to different types of shocks, such as terrorism (see, e.g. Araña and León, 2008; Liu and Pratt, 2017; Samitas et al., 2018; Bassil et al., 2019), natural disasters (among others, see Tsai and Chen, 2011; Rosselló et al., 2020; Strobl et al., 2020) , and pandemic crises (e.g. SARS flu, and Covid-19 pandemic) (see, among others Au et al., 2005; Kuo et al., 2008; Barcaccia et al., 2020; Li et al., 2020; Polyzos et al., 2020; Uğur and Akbıyık, 2020; Zhang et al., 2020; Gössling et al., 2021).

Here, we focus on the effect of the Great recession on Italian inbound tourism. The financial and economic crisis which began in 2007 in the USA had a severe impact on the world economy, and hence on tourism. Indeed, as reported by EUROSTAT (2010), nights spent by non-residents in the EU-27 Eurozone suffered a decrease of 7.7% in 2009.

The impact of recessionary shocks on tourism has been explored over recent decades (see, among others Prideaux and Witt, 2000; Okumus et al., 2005; Wang, 2009; Perles-Ribes et al., 2016), including research on the effect on tourism of the Great recession (see e.g. Smeral, 2009, 2010; Song et al., 2010; Song and Lin, 2010; Ritchie et al., 2010; Haque and Haque, 2018).

This chapter can be inserted in this stream of literature and aims: *i)* to evaluate how Italian regions react to the Great recession and *ii)* to explore if the ability to cope with the crisis differs across regions. This reminds us of the well-known concept in regional science of resilience, which can be defined as the ability of a region to resist economic shocks and recover from them (among others, see Östh et al., 2015; Hudec et al., 2018; Faggian et al., 2018; Cellini and Cuccia, 2019; Urso et al., 2019). However, both the impact and the way in which the crisis hit tourism may differ across destinations, and hence, their ability to cope may differ too. Research into this phenomenon, therefore, is extremely important for destination managers and policy makers. Indeed, understanding determinants of destination resilience enables tourism managers to adopt suitable strategies to reduce the impact of similar future shocks on destination attractiveness and to recover faster.

The concept of resilience was first introduced in physics and rapidly applied in different fields, such as biology, ecology, psychology, sociology, and economics.[1] Traditionally, the concept of economic resilience has been applied to economic variables, such as Gross Domestic Product (GDP), Value Added (VA), Employment, and Annual Wages (see e.g. Martin, 2012). However, as argued by Martin et al. (2016) *"The basic idea of resilience is that it captures how an entity or system reacts to and recovers from an adverse disruption"* (p. 564). Therefore, the resilience of tourist destinations may be interpreted as the ability of destinations to keep their attractiveness during a recession and to restore their attractiveness after the shock.

As mentioned above, we focus on Italian inbound tourism demand. Italy is an interesting case study for different reasons. First, it is one of the top cultural destinations in the world; more than 38% of inbound tourists choose Italy for its cultural, artistic and archaeological heritages, e.g. UNESCO world heritage sites, museums and similar attractions (OECD, 2011, p. 110). Second, tourism is very important for the Italian economy. The valued added of the tourism industry, in 2017, made up 6% of the Italian value added ISTAT (2020b).[2] Lastly, the impact of the Great recession on Italian tourism has actually received little attention, to the best of our knowledge, the only attempts being the studies by Cellini and Cuccia (2015) and Bernini et al. (2020). Cellini and Cuccia (2015) measure the resilience of the Italian tourism industry in the face of the recent financial crisis at NUTS2 level. Bernini et al. (2020) measure its resilience to crisis shocks from both macro and micro perspectives by means of expenditure elasticities.

The aim of this chapter is twofold. First, it aims to explore differences in the resistance and recovery of Italian destinations and secondly to evaluate whether the resilience of destinations is related to their industrial structure and if so, how.

We have adapted to the field of tourism, the theoretical framework on economic resilience proposed by Doran and Fingleton (2018), who analyse differences in the impact of the Great recession on employment in the US Metropolitan Statistical Areas. Their

[1]For an overview on the concept of resilience, see Bhamra et al. (2011) and Reid and Botterill (2013). For a detailed discussion on resilience from a regional science perspective, see Modica and Reggiani (2015) and Modica et al. (2019).

[2]The latest available Italian Tourism Satellite Account (TSA) was carried out by the Italian Institute of Statistics (ISTAT) in 2020. The data refer to the tourist industry in 2017.

approach is based on the estimation of a dynamic spatial panel model, which provides a prediction equation to generate a no-crisis counterfactual of employment. They then use these counterfactual predictions to evaluate the resilience of US Metropolitan Statistical Areas. In our study, we use the Dynamic Spatial Durbin Model with common factors described in Chapter 3 to obtain a counterfactual of inbound tourism demand series for the 110 Italian provinces, which will provide a yardstick for evaluating the resilience of Italian tourist destinations to the Great recession shock.[3] More precisely, the prediction of the model in Chapter 3 is used to generate a counterfactual of tourism demand, which is the expected level of tourism demand, had the crisis not occurred. Based on this quantity, similarly to Doran and Fingleton (2018), we measure the resilience of Italian destinations by comparing the actual tourism demand with its counterfactual. To explore the relationship between the resilience of Italian destinations and their industrial structure just before the onset of the adverse shock we perform a regression analysis in which resilience measures (i.e. resistance and recovery) are the dependent variables.

The relationship between economic resilience and industrial structure has been widely explored in economics literature (Martin, 2012; Fingleton and Palombi, 2013; Doran and Fingleton, 2014; Giannakis and Bruggeman, 2017; Kitsos and Bishop, 2018; Martin and Gardiner, 2019). Martin et al. (2016) discussed the importance of the makeup of industry as a possible factor affecting resilience. Doran and Fingleton (2018) explored the hypothesis that differences in industrial structure may affect resilience to the crisis, finding that specialization had a negative effect on resistance but a positive effect on the ability to recover from the shock. This aspect of resilience seems to be an unexplored area in the tourism field, and hence, this chapter is an attempt to fill this gap in the literature.

The chapter is structured as follows. In section 2, we provide an overview of the basic concepts of economic resilience. Section 3 describes the prediction methodology and our resilience measures. The analysis of determinants of resilience and interpretation of results is provided in Section 4. Section 5 concludes.

4.2 Economic resilience and measures

Economic resilience relates to the ability of economic systems to absorb the impact of an adverse event (e.g. an economic shock), and the ability to react and recover from the negative event. Martin (2010) distinguished three approaches of resilience, namely, engineering, ecological, and adaptive. Engineering resilience relates to the resistance of a system to shocks and how fast it is able to restore its pre-shock equilibrium, and hence

[3]The model specification used in this study, as discussed in Chapter 3, enables us to account for both the spatial and temporal dependence present in the data, and to account simultaneously for both supply and demand characteristics.

to 'bounce back' from the adverse event (Martin, 2012; Fingleton et al., 2012; Simmie and Martin, 2010). This approach to economic resilience is based on the assumption that shocks do not have a permanent effect on a system's performance. Holling (1973), firstly, introduced ecological resilience in ecological sciences, referring to it as the magnitude of shock the system is able to absorb before moving to another steady state. It differs from engineering resilience because it assumes that systems may have multiple stable states. However, as noted by Martin (2012), from the definition, it is not fully clear whether measuring ecological resilience should be by the size of the shock or by the ability of a system to reach a new equilibrium. This latter notion of resilience assumes that the adverse shock has permanent effects on the growth path of a system, and that the new configuration may be either 'better' or 'worse' than the pre-shock one. Therefore, as argued by Martin (2012), there is a close relationship between ecological resilience and the concept of hysteresis, as defined by Romer (2001). Finally, a third kind of resilience is termed adaptive resilience. It can be seen as the ability of a system to adapt its structure to react to an adverse shock and to maintain core performances (Martin, 2012; Martin and Sunley, 2015). The adaptive approach considers resilience as a dynamic process of resistance and adaptation in response to external shocks, and regions are considered as complex adaptive systems. As noted by Martin (2012), the ways regions adapt over time, and the reasons why some of them are more able to adapt than others are key sources of resilience.

Martin (2012) identified four components or aspects of regional economic resilience, namely: resistance (the degree of vulnerability to the shock), recovery (the speed and extent of recovery from the shock), reorientation (the degree of structural reorientation of a regional economy), and renewal (the extent to which the regional economy restores the growth path before the shock). Martin and Sunley (2015), in their comprehensive work on regional resilience, highlight the multifaceted nature of resilience, and put forward the view that the four aspects of resilience are sequential and recursive. Martin and Sunley (2015) and Martin et al. (2016) note that the four components of resilience depend on various factors, such as extent and duration of the shock, the pre-shock growth path, and determinants of the growth path; among these determinants we mention the economic structure.

Martin and Sunley (2015) identify four main approaches to measuring regional economic resilience found in the literature. They include the case study approach (see, e.g. Simmie and Martin, 2010), the resilience indices approach, which measures resilience by using key variables of interest (see, among others Martin, 2012), time series models, which estimate the time needed to absorb the impact of the shock (see Fingleton et al., 2012), and causal structural models, which generate counterfactual series if the shock had not occurred (see, Fingleton and Palombi, 2013; Doran and Fingleton, 2015; Fingleton et al., 2015; Doran and Fingleton, 2018). As stated in the introduction, this chapter focuses on this latter approach. However, Martin and Sunley (2015) conclude that: *"there is no single agreed approach to measuring the 'anatomy' of regional (or local or city) resilience. Defining resistance and recovery is in fact far from straightforward"* (pp. 16-18).

In this study, we focus on measuring the first two components of resilience (i.e. resistance and recovery), and we seek to explore if and how the economic structure of Italian destinations may have affected their resilience to the Great recession, controlling for variables related to the tourist vocation of the Italian provinces.

4.3 Data

Exploiting the estimates of the model of inbound tourism demand in Italy described in Chapter 3, we measure the economic resilience of the 110 Italian provinces (NUTS3 regions). To explore determinants of resistance and recovery, we use the data on the number of employees of local business units by sector, provided by the Italian Institute of Statistics (ISTAT), and data on the classification of local administrative units (municipalities) in terms of tourist vocation provided in a recent publication by ISTAT (ISTAT, 2020a).[4] Data on employees of local business units, used to compute industry structure indices, refer to 2007, in order to have a measure just before the onset of the crisis, and hence it is reasonable to consider measures based on this data as exogenous, as did Doran and Fingleton (2018). The data on tourist vocation provided by ISTAT are at municipal level; therefore, exploiting this classification we constructed a classification of Italian NUTS3 regions based on quantiles. The description of the construction of this classification is to be found in Section 5.

4.4 Counterfactual tourism demand and destination resilience

As mentioned before, to measure the two components of resilience (i.e. resistance and recovery) we compare the observed values of tourist flows with counterfactual predictions. The counterfactual of tourism demand is the expected level of tourist flows,

[4] On the basis of the Italian Law 77/2020, the Italian Institute of Statistics, has defined a classification of municipalities based on their tourist attractiveness. Specifically, different tourist vocation and attractiveness indicators for the year 2019 have been provided. As tourist vocation variable is concerned, it is assessed on the basis of the geographical and anthropic characteristics of the municipality (e.g. leght of coast, number of cultural sites, etc.). After identifying the function (i.e. vocation), the municipality is classified touristic or not if it records a number of yearly nights spent greater to the first decile of the total nigths spent in the whole municipalities having the same function. Therefore, taking into account as the tourist vocation variable has been defined, it is reasonable to think that it has not changed significantly over time.

had the crisis not occurred. The starting point in generating this counterfactual is the prediction of (log) tourism demand from the model described in Chapter 3 after the crisis shock (i.e. 2009-2013). This prediction methodology involves the parameter estimates of such a model (denoted by $\hat{\bullet}$), the prediction of which reads as follows:

$$\begin{gathered}\widehat{ns}_{ijt} = \hat{\tau} ns_{ijt-1} + \hat{\rho} Wns_{ijt} + \hat{\eta} Wns_{ijt-1} + \hat{\beta}_1 p_{ijt} + \hat{\beta}_2 v_{ijt} + \\ \hat{\beta}_3 D_{ij} + \hat{\beta}_4 T_{it} + \hat{\beta}_5 Tm_{it} + \hat{\beta}_6 Pre_{it} + \hat{\beta}_7 Bank_{it} + \hat{\beta}_8 Transp_{it} + \\ WX\hat{\boldsymbol{\theta}} + \hat{\boldsymbol{\Gamma}}_{\mathbf{1}} \overline{ns}_{jt} + \hat{\boldsymbol{\Gamma}}_{\mathbf{2}} \overline{ns}_{jt-1} + \hat{\mu}_i + \hat{\mu}_j\end{gathered} \tag{4.1}$$

where, the estimated expectations of (log) nights spent ($\widehat{ns}_{ijt}$) depend on the observed (actual) nights spent in each destination and on those in the neighbourhood from each origin at both time t and $t-1$, on relative price (p), relative value added (v), geographical distance in km between origin and destination (D), weather conditions of destinations (maximum temperature (T), minimum temperature (Tm), amount of precipitations (Pre)), number of bank branches ($Bank$), demand for public transport ($Transp$) of destinations, and finally on the spatial lag of the previous covariates (WX). We account for strong cross-sectional dependence in the data with common factors approached by cross-sectional averages of the dependent variable at time t and $t-1$. Unobservable characteristics of destinations and origins are accounted for by including origin and destination fixed effects (μ_i and μ_j respectively).

Since the aim is to estimate a no crisis counterfactual of tourist flows ($\widetilde{ns}_{ijt}$), we need to consider counterfactual levels of relative price and relative value added, denoted respectively by $\tilde{p}_{ijt}$ and $\tilde{v}_{ijt}$. Therefore, the prediction Equation 4.1 will be as follows:

$$\begin{gathered}\widetilde{ns}_{ijt} = \hat{\tau} ns_{ijt-1} + \hat{\rho} Wns_{ijt} + \hat{\eta} Wns_{ijt-1} + \hat{\beta}_1 \tilde{p}_{ijt} + \hat{\beta}_2 \tilde{v}_{ijt} + \\ \hat{\beta}_3 D_{ij} + \hat{\beta}_4 T_{it} + \hat{\beta}_5 Tm_{it} + \hat{\beta}_6 Pre_{it} + \hat{\beta}_7 Bank_{it} + \hat{\beta}_8 Transp_{it} + \\ WX\hat{\boldsymbol{\theta}} + \hat{\boldsymbol{\Gamma}}_{\mathbf{1}} \overline{ns}_{jt} + \hat{\boldsymbol{\Gamma}}_{\mathbf{2}} \overline{ns}_{jt-1} + \hat{\mu}_i + \hat{\mu}_j\end{gathered} \tag{4.2}$$

We considered a no-crisis counterfactual of relative price and value added, and of their spatial lag, assuming that these two variables have been directly affected by the Great recession. The mechanism employed to compute the counterfactual series of these two variables is described below. The assumption that the other explanatory variables are not affected by the crisis is theoretical, and is based on the idea that, for such variables, the crisis could not be considered the main source of change. While distance and climate variables are not likely to have been affected by the crisis, others, like the number of bank branches and the demand for public transport might have been. In the case of banks, however, it is assumed that the number of bank branches is affected by many other factors (e.g. the advent of online banking), and hence, the change in this variable is not totally ascribable to the crisis. As far as the demand for public transport is concerned, it is assumed that the crisis is not likely to have had much impact on this variable since the cost of public transport in Italy is a political decision made by public institutions and is usually lower than the market price. The low sensitivity of public transport to the crisis may be determined, among other factors, by the fact that people need to get around cheaply. The increasing attention to sustainability and the ecological impact of human activities may also be a boost for using public transport, and hence, reduce the negative effects of the crisis on the demand for public transport.

Generating a counterfactual of price and value added

The problem of obtaining a counterfactual for price and value added is how to compute the expected value that these variables may have had in the absence of the economic crisis. Doran and Fingleton (2018), compute the counterfactual of explanatory variables assuming that output in a region would change at the national rate, and hence, the counterfactual of output (the explanatory variable of their study) is generated by multiplying output levels with the growth rate of national GDP.

However, we assume that values of price and value added of each region would have followed the regional pre-crisis trend if the crisis had not occurred, and hence, we generate the counterfactual of these explanatory variables with predictions of the pre-crisis trend for the post-crisis period. Therefore, following the approach employed by Doran and Fingleton (2015), the modelling approach is preferred to generate counterfactuals. In our case, the counterfactuals of the two variables for each origin-destination pair are based on a panel data model with region-specific coefficients, for which the general equation reads as follows:

$$y_{it} = \alpha_i + \beta_i x_{it} + \varepsilon_{it} \tag{4.3}$$

Since the relative value added is computed as the ratio between the value added of each destination and that of each origin, we firstly compute the counterfactual of the numerator and the denominator separately, and then compute the ratio. In the light of our hypothesis, that the pre-crisis trend will continue in the post-crisis period in the absence of shocks, the value added of destinations and origins have been regressed on a time index, as shown in the following equations:

$$v_{it} = \alpha_i + \beta_i time + \varepsilon_{it} \tag{4.4}$$

where v_{it} is the value added (log) of destination i at time t, with $i = 1, \ldots, 110$ and $t = 2000, \ldots, 2007$; $time$ is the time index and takes values $2000, \ldots, 2007$. α_i is the destination-specific intercept, and ε_{it} the error term of destination i at time t.
The same model specification has been used to model the value added (log) of origins,

$$v_{jt} = \alpha_j + \beta_j time + \varepsilon_{jt} \tag{4.5}$$

where $j = 1, \ldots, 23$ identifies the countries of origin.
Equations (4.4) and (4.5) are estimated for the period 2000-2007 and used to generate predicted values for the period 2008-2013. These values give an estimate of the expected value added in the absence of the crisis for both destinations and origins. The counterfactual of value added (log) of each origin-destination pair at time t ($\tilde{v}_{ijt}$) is computed as the ratio between these predicted values, as shown below:

$$\tilde{v}_{ijt} = \frac{\hat{v}_{it}}{\hat{v}_{jt}} \tag{4.6}$$

The same procedure has been used to estimate the counterfactual of relative price (log), which we computed as the ratio between the consumer price index (CPI) of destination and the CPI of origin. Therefore, the counterfactual of relative price ($\tilde{p}_{ijt}$) is computed as the ratio between the predicted CPI of destination ($\widehat{CPI}_{it}$) and the predicted CPI of origin ($\widehat{CPI}_{jt}$) for 2008-2013, as follows:

$$\tilde{p}_{ijt} = \frac{\widehat{CPI}_{it}}{\widehat{CPI}_{jt}} \tag{4.7}$$

This procedure of estimating counterfactual series has both advantages and disadvantages. The main drawback of this approach is the relatively short period of the analysis, which might affect the robustness of the forecasts. The main advantage, however, is that the forecasts are based on the trend of actual data over the period under study.

Destination resilience to the Great recession

As previously mentioned, we focus on two components of resilience, namely resistance and recovery (Martin, 2012; Martin and Sunley, 2015; Martin et al., 2016). Since resistance is the ability of a region to absorb the impact of the crisis shock, it is measured in the contraction period, i.e. 2008-2009. Since recovery is the ability to recover from the adverse shock, it is measured in the expansion period, i.e. 2010-2013. Following Martin et al. (2016) and Doran and Fingleton (2018), we measure the two elements of resilience as shown in the following equations:

$$Res_i = \frac{\nabla ns_i^D - \nabla \widetilde{ns}_i^D}{ns_i^{2007}} \tag{4.8}$$

where, ∇ns_i^D is the change in nights spent in destination i during the downturn of the Great recession, and $\nabla \widetilde{ns}_i^D$ is the change in the counterfactual of nights spent in destination i during contraction. Since the focus is on a relative measure of resilience, differences between observed and counterfactual tourist flows are divided by nights spent in destination i in 2007 (ns_i^{2007}).

$$Rec_i = \frac{\nabla ns_i^R - \nabla \widetilde{ns}_i^R}{ns_i^{2007}} \tag{4.9}$$

where, ∇ns_i^R is the change in nights spent in destination i during the recovery period after the Great recession shock. $\nabla \widetilde{ns}_i^R$ is the change in the counterfactual of nights spent in destination i during recovery. Similarly to resistance, differences between observed and counterfactual tourist flows are divided by nights spent in destination i in 2007 (ns_i^{2007}).
The choice of 2007 to scale resilience measures comes from the assumption that 2007 can be considered as the onset of the Great recession, and hence, dividing the two measures of resilience by tourist flows in 2007 enables us to account for the level of tourism demand at the beginning of the crisis.

4.5 Determinants of destination resilience

To explore the main determinants of resistance and recovery, we consider two groups of variables, those related to the economic structure of regions and those related to tourist vocation. The variables of economic structure include the location quotient index, the Herfindahl-Hirschman Index (HHI), and a proxy of the level of urbanization. The location quotient ($LQ_{i,2007}$) measures the level of concentration of an industry (e.g. tourism) in a region, comparing the region to the nation. When the location quotient equals 1 the share of an industry is the same as that of the nation; if the location quotient is greater than 1, this share is greater than in the country as a whole. We computed the location quotient of the 110 Italian provinces on the number of employees in tourist activities for the year 2007 (NACE codes: I55 and I56), as follows:

$$LQ_{i,tour,2007} = \frac{E_{i,tour,07}/E_{i,07}}{E_{tour,07}/E_{07}} \tag{4.10}$$

where, $E_{i,tour,07}$ is the number of employees in tourism in region i in 2007, and $E_{i,07}$ is the total number of employees in region i in 2007. $E_{tour,07}$ is the number of employees in tourism nationally in 2007, and E_{07} is the total number of employees in the nation in 2007.
The Herfindahl-Hirschman Index (HHI), which measures the specialisation of the economy of each province, ranges from $1/N$ (where N is the number of sectors) in the case of the same share in all sectors, to 1 in the case of maximum specialisation (only one sector in a region), and hence, the higher the HHI, the more specialised a region is. It is computed as the sum of the square of sector shares of a region, as in the following equation:

$$Her_{i,07} = \sum_{j=1}^{N} s_j^2 = \sum_{j=1}^{N} \left(\frac{E_{i,j,07}}{E_{i,07}} \right)^2 \tag{4.11}$$

where, $E_{i,j,07}$ is the number of employees in sector j of region i in 2007, and $E_{i,07}$ is the total number of employees in region i in 2007. This index is based on employees of local business units in the 110 Italian provinces across 17 different sectors.

The urbanization level (Urb_i) is measured by the population density of each region in 2007. To distinguish between rural and urban regions, we use the distribution in quantiles in order to avoid sources of arbitrariness in the study (see Piacentino et al., 2017a). Therefore, we have an ordinal variable with four levels based on the quantiles of population density, where 1 indicates low urbanization and 4 a high level of urbanization.

Since the Location Quotient and the Herfindahl-Hirschman Index measure the level of specialization, we believe these variables may be used to assess the hypothesis that the industrial structure of a destination may affect its resilience. Furthermore, the aforementioned variables are based on 2007 data (i.e. just before the onset of the crisis), and hence, it is reasonable to treat them as exogenous.

The second group of variables (tourism vocation) is introduced in the analysis to control for the effect of tourist vocation on resilience, and to reduce concerns with omitted variables. They are dummy variables defined in line with a recent publication from the Italian Institute of Statistics (ISTAT, 2020a) that provides a classification of local administrative units (municipalities) in terms of tourist vocation. By considering different regional characteristics, (e.g., number of UNESCO sites, length of coast, number of natural protected areas, etc.), ISTAT identified different types of tourist vocation (for more details, see ISTAT, 2020a). We consider 6 categories of tourism vocation based on ISTAT, which are: *(i) 'provinces with a cultural, artistic, and landscape vocation', (ii) 'provinces with a sea tourism vocation', (iii) 'provinces with a mountain tourism vocation', (iv) 'provinces with a sea tourism and cultural, artistic, and landscape vocation', (v) 'provinces with a mountain tourism and cultural, artistic, and landscape vocation', (vi) 'tourist provinces that do not belong to any of the previous categories'*. We classify each of the 110 Italian provinces in one of these six categories based on the classification of municipalities. More specifically, we assign *i-th* province to the *j-th* category if the number of municipalities in that province in that category is equal to or greater than the median number of municipalities in the same category at national level. Simply put, we assign province i to category (j) if the number of municipalities of *i-th* province in category (j) is greater than or equal to the national median number of municipalities in category (j).

To explore the determinants of destination resilience, we perform a regression analysis where the two measures of resilience (resistance and recovery) are the dependent variables in the regression models. The Location Quotient, the Herfindahl-Hirschman

Index, and the level of urbanization are the main explanatory variables for exploring the effect of industrial structure at the onset of the crisis on resilience. Furthermore, we control for tourist vocation to reduce omitted variable bias. Therefore, the two models are the following:

$$Res_i = \alpha + \beta_1 LQ_{i,tour,07} + \beta_2 Her_{i,07} + \beta_3 Urb_{i,07} + \gamma TourVocation_i + \varepsilon_i \tag{4.12}$$

where, Res_i is the resistance of destination i, $LQ_{i,tour,07}$ is the location quotient of tourist activities in destination i in 2007, $Her_{i,07}$ is the Herfindahl-Hirschman Index of destination i in 2007, $Urb_{i,07}$ is the level of urbanization, with values from 1 to 4; the first level enters the model as the baseline and the other levels are compared to the first. $TourVocation_i$ are dummies of tourist vocation as previously described. Finally, ε_i is the error term, which is assumed iid $(0, \sigma^2)$.

We used the same model specification to explore recovery, which reads as follows

$$Rec_i = \alpha + \beta_1 LQ_{i,tour,07} + \beta_2 Her_{i,07} + \beta_3 Urb_{i,07} + \gamma TourVocation_i + \varepsilon_i \tag{4.13}$$

where, Rec_i is the recovery measure of destination i.

We have compared various model specifications and have carried out a modelling selection procedure based on the information criteria, that is the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC).

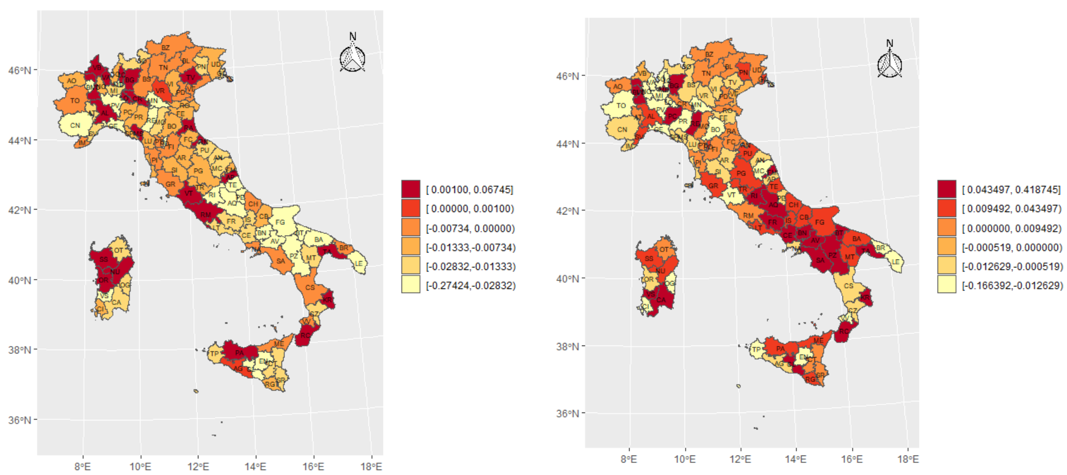
4.6 Results

4.6.1 *The Resilience of Italian destinations*

Figure 4.1 shows quintiles of the two elements of resilience, viz. resistance (panel a) and recovery (panel b).[5] Values of resistance (on the left hand side), show that the number of destinations that resisted well to the crisis shock (darker areas) is small, and most of these are in the North-East of Italy. However, there are also some destinations with high values of resistance in the Centre and South of Italy (e.g. Rome, Viterbo, Taranto, Reggio Calabria, Palermo), and the local cluster in the North of Sardinia is also

[5] We adapted quintiles to separate negative values from positive ones. To do this we split the fourth quintile classes of resistance and the third quintile classes of recovery into two sub-classes in order to distinguish between negative and positive values.

noteworthy (i.e. Sassari, Nuoro, and Oristano). These areas have been able to face the negative effect of the crisis. Nevertheless, the majority of Italian destinations have not been able to absorb the crisis shock; indeed, they have negative values of resistance, indicating a reduction of tourism demand during the crisis compared to 2007. As far as recovery is concerned (Figure 4.1, panel b), we note that almost all the destinations in the South with highly negative resistance show high values of recovery (darker areas), indicating that these destinations have a higher tourism demand than the no-crisis counterfactual. This means that these destinations suffered greatly, but in the post-crisis period, have been able to activate resilience mechanisms to cope with the crisis, and to improve their attractiveness. We also observe a cluster of regions with low but positive values of recovery in the North-East of Italy (e.g. Bolzano, Trento, Belluno, and Udine), indicating that actual tourist flows are close to the expected ones in the absence of the crisis. Therefore, these destinations recovered from the crisis, but they have not been able to make gains in terms of attractiveness. The business tourism area around Milan shows high negative values of recovery (light areas), indicating that these destinations have not been able to recover from the shock, probably because the crisis seriously affected business tourism.



(a) Resistance (b) Recovery

Figure 4.1: Quintiles of resilience measures, resistance on the left (a) and recovery on the right (b).

Putting together the information from the two maps in Figure 4.1 it is possible to classify Italian tourism destinations in terms of resilience. To do this we consider the interpretative scheme shown in Figure 4.2 where we label resilient, tourist destinations with positive values of both resistance and recovery. These are destinations with the ability not only to absorb (resistance), but also to recover from the adverse shock. Destinations with negative values of both resistance and recovery are labelled not resilient. These destinations are vulnerable to the crisis and unable to recover from the shock. If resistance is positive, which indicates a good ability to absorb the shock, and recovery is negative, we have resistant destinations, while destinations with positive recovery, but negative resistance are likely to have good recovery ability.

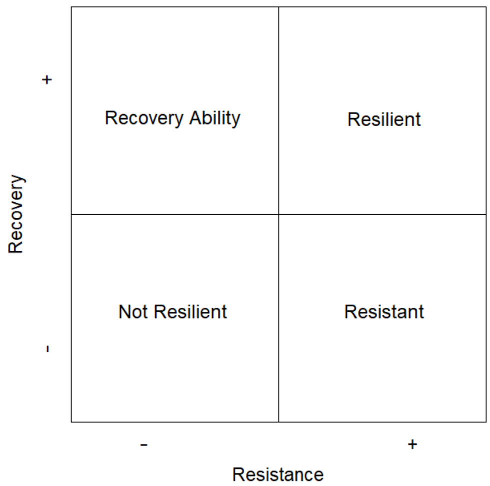


Figure 4.2: Interpretative scheme of destinations' resilience

Figure 4.3 shows the classification of Italian tourism destinations based on the aforementioned interpretative scheme of resilience. It reveals only 13 resilient destinations which can be considered the best performing destinations in terms of resilience. This group includes well-known coastal and cultural destinations in the Centre and South of Italy, like Rome, Taranto, Crotone, Reggio Calabria, Palermo, Sassari, and Nuoro. It also includes Ravenna and Rimini, two traditional coastal and/or cultural destinations in the North-East of Italy, in addition to some traditional business tourism destinations including Novara, Alessandria, Bergamo, and Cremona.

More than 45% of destinations (51 out of 110) are in the 'recovery ability' category. Most of these destinations are in the South and others in the North-East of Italy, and include a varied group of destinations. Some of them are typical skiing destinations (e.g. Bolzano, Trento, and Belluno), whereas others are well-known coastal and cultural destinations (e.g. Pisa, Firenze, Salerno, Bari, Foggia, Messina, Catania, Syracuse, Cagliari, etc.).

There are 11 regions with positive values of resistance and negative recovery. We classified these regions as resistant. This is a varied group of well-known coastal and cultural destinations, and a handful of mountain destinations including Verbano-Cusio-Ossola,

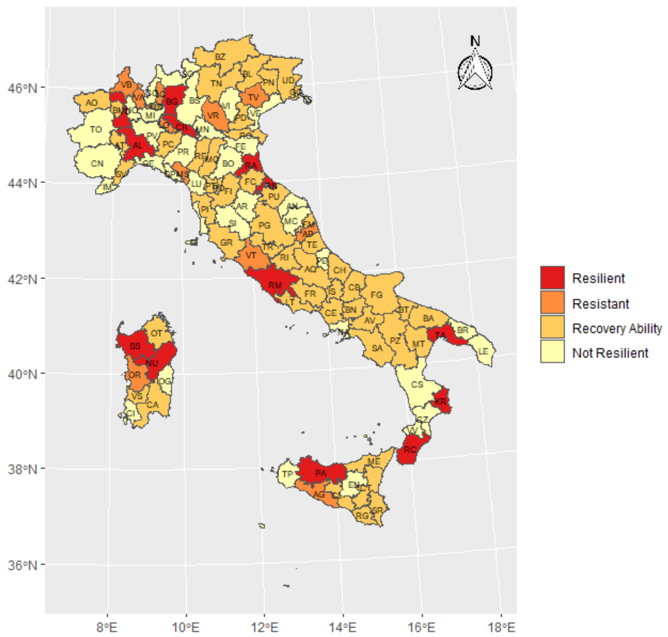


Figure 4.3: Resilience of Italian tourism destinations

and Varese. Some of the regions in this group are traditional cultural destinations, like Verona, and Viterbo. These are appealing destinations with important local attractors including the UNESCO heritage site of Verona city and the *Arena di Verona* in Verona, and *Palazzo Farnese*, *Necropolis Tarquinii*, and *Palazzo dei Papi* in Viterbo. Natural tourism and coastal destinations, include places like Agrigento, Oristano, and Ascoli Piceno.

Finally, we come to the 35 destinations that are not resilient. These regions, most of which are in the North, are vulnerable to the crisis in terms of tourist attractiveness, with little ability to cope with the crisis shock, or to improve their attractiveness through resilience mechanisms. Among these are well-known coastal and cultural tourist destinations like Venice, Bologna, Ferrara, Genova, Siena, and Trapani and business destinations such as Turin, Novara, Pavia, and Brescia.

These results show us the differences among Italian tourism destinations in terms of resistance and recovery to the Great recession shock. In the light of that, it is important to investigate the main factors affecting destination resilience, providing an explanation for the differences. The next subsection provides results of a regression analysis approach that attempts to explore this issue.

4.6.2 *Factors affecting resilience*

Table 4.1 gives the estimates of equations (4.12) and (4.13), that is the two linear regression models of resistance and resilience with all the covariates described in Section 5. We computed the Variance Inflation Factor (VIF) of both models to test the presence of multicollinearity issues. Since the VIFs of the two models are not far from one (1.156 for resistance and 1.201 for recovery), we can reasonably assume there are no relevant multicollinearity issues.

Table 4.1: Full models estimates of resistance and recovery [a]

Variables	**Resistance**		**Recovery**	
	Estimate	Std. Error	Estimate	Std. Error
(Intercept)	-0.1032 **	0.0368	0.1300 *	0.0647
$LQ_{i,tour,07}$	0.0223 .	0.0126	-0.0280	0.0222
$Her_{i,07}$	0.3136 .	0.1767	-0.3124	0.3106
$Urb2$	-0.0185	0.0140	0.0153	0.0245
$Urb3$	-0.0023	0.0131	-0.0117	0.0229
$Urb4$	0.0075	0.0133	-0.0498 *	0.0234
$Vocation(i)$	0.0234 *	0.0105	-0.0408 *	0.0185
$Vocation(ii)$	0.0154	0.0115	-0.0336 .	0.0202
$Vocation(iii)$	-0.0037	0.0117	0.0069	0.0205
$Vocation(iv)$	0.0056	0.0130	0.0013	0.0229
$Vocation(v)$	-0.0092	0.0133	-0.0186	0.0233
$Vocation(vi)$	0.0047	0.0094	0.0134	0.0165
AIC	-364.23		-240.17	
BIC	-329.13		-205.07	
VIF	1.156		1.201	
Adj. R-squared	0.038		0.074	
R-squared	0.135		0.167	

[a] ** $p < 0.01$, * $p < 0.05$, . $p < 0.1$

Starting from these models, we performed a stepwise model selection procedure based on information criteria (AIC and BIC) in order to select the best performing model of both resistance and recovery taking into account the more suitable informative structure.

Table 4.2 shows the estimates of the preferred models.

Table 4.2: Selected models estimates of resistance and recovery [a]

Variables	**Resistance**		**Recovery**	
	Estimate	Std. Error	Estimate	Std. Error
(Intercept)	-0.1029 **	0.0356	0.1366 *	0.0626
$LQ_{i,tour,07}$	0.0222 .	0.0112	-0.0327	0.0197
$Her_{i,07}$	0.3141 .	0.1746	-0.3148	0.3073
$Urb2$	-0.0154	0.0134	0.0211	0.0235
$Urb3$	0.00014	0.0126	-0.0082	0.0222
$Urb4$	0.0107	0.0127	-0.0446 *	0.0223
$Vocation(i)$	0.0208 *	0.0099	-0.0451 *	0.0174
$Vocation(ii)$	0.0177 .	0.0104	-0.0313 .	0.0183
$Vocation(iii)$	-0.0054	0.0107	0.0053	0.0189
AIC	-369.24		-244.90	
BIC	-342.23		-217.90	
VIF	1.156		1.201	
Adj. R-squared	0.0582		0.091	
R-squared	0.127		0.158	

[a] ** $p < 0.01$, * $p < 0.05$, . $p < 0.1$

As far as resistance is concerned (shown in the second and third columns), the location quotient of tourist activities and the Herfindahl-Hirschman Index (HHI) are not significant at 5%, but are at 10%. Both indices seem to have a positive effect on destination resistance, indicating that a more specialized structure increases the ability to absorb the shock. Furthermore, higher levels of urbanization than the baseline (first quartile) seem not to have a significant effect on resistance. Conversely, looking at recoverability the coefficients of the two industry structure indices are negative, but not significant at a level of 5%. The negative and significant effect of the fourth level of urbanization suggests that highly urbanized regions ($Urb4$) seem to have lower recoverability than rural areas (baseline).

As far as tourist mission variables are concerned, the estimates indicate that a mountain tourist vocation does not have a statistically significant effect on either resistance or recovery. Cultural, artistic and landscape tourist vocation category *(i)* is significant in both models and acts positively on resistance, but negatively on the ability to cope with the crisis. We find similar results in the case of destinations with a sea tourist vocation, but with lower level of significance (at 10%). This suggests that cultural and sea destinations may benefit from higher resistance to the crisis, but may have less ability to react to the shock.

In summary, the regression analysis shows that destinations with a local concentration of tourism activities and a more specialized industrial structure are more resistant to the crisis than destinations with a low concentration of tourism activities and a diversified structure. In contrast, the local concentration of tourism activities and specialization in regional economies in the post-crisis period reduces their ability to restore pre-crisis tourism attractiveness, but this evidence must be carefully interpreted, since the estimate is not significant. In addition, the vocation of tourist destinations aids resistance to the crisis, but may have negative effects on their ability to recover.

4.7 Conclusions

This study explores the resilience of Italian tourist destinations to the shock of the Great recession and investigates the main determinants of such resilience. In doing so, adapting the theoretical framework used by Doran and Fingleton (2018) to tourism, it is the first attempt to analyze regional economic resilience at NUTS3 level and to propose a measure of resilience in terms of resistance and recovery.

Looking at resistance and recovery simultaneously, we cluster regions in resilient and not resilient categories. The resilient regions are those with positive values of both resistance and recovery, whereas not resilient regions have negative values of resistance and recovery. Intermediate cases may occur when the two elements of resilience have opposite signs. Results indicate differences among destination resilience. There are only 13 regions that can be seen as the ‘best’ in terms of resilience. These are varied well-known cultural and coastal destinations. We also find that more than 45% of regions are able to recover from the crisis shock, most of these, including some emerging destinations, being in the South and Centre of Italy. In the light of these differences, we performed a regression analysis to investigate the main factors affecting the resilience of Italian tourist destinations. Our key findings are that a higher local concentration of tourism activities and a more specialized structure of the economy increase the ability of a destination to absorb the shock, and hence, to be less severely affected by the crisis. Furthermore, destinations with a sea and cultural tourist vocation are likely to be more resistant, but less able to recover.

This study provides useful information to help destination managers to make their destinations less vulnerable to shocks, and provides them a roadmap of the key elements of destination resilience. On the one hand, the analysis highlights the weaknesses of some regions, which are sensitive to the crisis shock and poor in terms of recoverability. On the other hand, it reveals opportunities for some other areas that Destination Management Organisations (DMOs) should take into consideration when they create policies. This is the case of destinations with a good performance in terms of recovery, but which are highly sensitive to shocks. In such cases, destination managers should implement suitable policies to increase resistance to shocks. Managers in regions with best performing destinations in terms of resilience in the neighbourhood should try to benefit from their presence by creating socio-economic relationships with them in order to trigger positive spatial spillover effects.

Since our approach to measuring tourist resilience can be extended to other territorial areas, it is our intention to apply this approach to other destinations with territorial characteristics similar to Italy in order to compare results. Furthermore, the theoretical framework used in this study can be adapted to explore the effects of other kinds of shocks, such as that due to the Covid-19 pandemic. However, we could obtain more accurate results, if further data at NUTS3 level were available on cultural assets (e.g. museums, theatres, UNESCO heritage sites, art and film exhibitions, cultural organizations, etc.), natural resources (natural parks, marine protected areas, urban green areas, quality of beaches, etc.), environment (e.g. pollution and air quality), human capital in the tourism sector, investments in the marketing and promotion of destinations, the quality of auxiliary services for tourism, accessibility of destinations (e.g. highways, railroads, ports, airports, bus connections, etc.), and level of safety.

Conclusions

This thesis contributes to the growing literature on spatial analysis of tourism demand within the origin-destination setting from both a methodological and an empirical viewpoint. Beginning with published reviews on the analysis of tourism demand, we firstly provide an overview of the main approaches and models to the analysis of tourism demand. These can be classified into four categories, that is time series models, econometric models, artificial intelligence models, and judgemental methods. It is surprising that all the recent reviews on tourism demand neglect the spatial dimension in the analysis of the phenomenon. In the light of that, Chapter 1 provides a detailed overview of studies on the spatial analysis of tourism identifying the gaps in the literature and highlighting the contribution of the thesis. We found that spatial models attracted little attention in the literature, especially within the Origin-Destination (O-D) framework. In this stream of literature, the panel data approach is relatively recent and limited. At the same time, we found that the decomposition method of spatial shift-share has not yet been applied to decompose tourist flows with both origin and destination information. To fill this gap in the literature, we propose a methodological refinement of spatial shift-share analysis that combines two existing streams of literature and apply it to inbound tourist flows in Italian NUTS3 regions by origin in order to explore the competitiveness of Italian tourist destinations. The proposed method enabled us to form a detailed picture of inbound tourism demand in Italy, which revealed differences in tourist competitiveness among NUTS3 regions. This method allows us to disentangle net spatial competitive and allocation effects at both regional and neighbourhood level, taking into account the industrial specialization effect. We found evidence of spatial spillover effects in some regions, which means they benefit from the presence of well-performing destinations in the neighbourhood. We also found some threats to the attractiveness of certain well-known Italian destinations because of their lack of ability to exploit tourist resources. Finally, we found some destinations that may not exploit their great tourist potential at all, because their performance may be negatively affected by unattractive destinations in the neighbourhood.

After this explanatory analysis on the competitiveness of Italian destinations, in the third chapter we carried out an econometric analysis of inbound tourism demand in Italy by means of a Dynamic Spatial Panel Data model with common factors (DSPD-WCF), applied within the O-D setting. The novelty of this approach is the inclusion, simultaneously, of time, spatial, and spatiotemporal effects, along with common factors within the O-D setting. This model, therefore, enables us, at the same time, to account for the information on both origin and destination of tourists, and to assess the presence of temporal and spatial dependence in tourist flows, as well as the presence of spatial spillover effects. The inclusion of common factors means the presence of strong cross-sectional dependence in the data can be controlled for. This study is a significant contribution since it makes for a better interpretation of spatial spillover effects controlling for the presence of strong cross-section dependence and the presence of spatial cointegration, in addition to unobserved push and pull factors fixed over time by including origin and destination fixed effects. This helps the complex spatial features of tourist flows to be understood better. As regards temporal dependence, we found a positive temporal effect, indicating the presence of positive habit formation, an explanation for the popularity of Italian destinations abroad. Furthermore, the positive sign of the spatial autoregressive coefficient points towards the fact that a destination may benefit from the presence of attractive regions in the neighbourhood. Another noteworthy result is the presence of significant direct and spillover effects of some covariates such as relative value added, indicating the level of development has a positive effect on tourist flows. This result suggests that the quality of services positively affects inbound tourist flows, as we consider the level of development as a proxy of the quality of services. We also find that warm destinations are preferred. The empirical evidence emerging from the analysis may be useful for Destination Management Organisations (DMOs) in planning market strategies to enhance destination attractiveness. For example, the positive effect of attractive neighbours indicates that a cooperation strategy with integrated and coordinated policies would improve the attractiveness of the entire territory.

Since the period of analysis includes the crisis shock due to the recent economic/ financial crisis (i.e. the Great recession), the last topic of this thesis explores differences in destination resilience to evaluate if and how the characteristics of a destination may affect its resilience. To accomplish this, we adapted to tourism the theoretical framework used by Doran and Fingleton (2018) for employment in the USA, and use the estimates of the model estimated in Chapter 3 to build a no-crisis counterfactual of tourism demand. In the first step of the analysis, we measured two elements of resilience (i.e. resistance and recovery) by comparing actual tourist flows with their counterfactual estimate. This gave us a detailed snapshot of the resilience of Italian tourist destinations to the severe shock of the Great recession, and showed up differences in how they coped. Looking at the two components of resilience jointly, that is, resistance and recovery, we identified four groups of destinations, namely resilient (the ‘best’), not resilient, resistant, and those with recovery ability.

Having discovered that the regions behave differently in terms of resilience, we next explored if and how destination resilience may be affected by the characteristics of the destination. To do this, we performed a regression analysis where resistance and recovery measures are the dependent variables. The location quotient of tourist activities, the Herfindahl-Hirschman Index (HHI), and the level of urbanization are the explanatory variables. We also control for the tourist vocation of each destination. Our key findings are that the local concentration of tourism activities and the level of specialization in a region have positive effects on its resistance. Our findings provide a detailed picture, including the main determinants, of the resilience of Italian destinations in terms of attractiveness. Destination Management Organisations (DMOs) and policy makers will find this information invaluable in planning appropriate strategies to reduce the vulnerability of tourist destinations to crisis shocks and to improve their recoverability.

In summary, the thesis provides a spatial analysis of inbound tourism demand in Italy that considers both origin and destination of tourists. We found that tourist competitiveness in Italy differs across destinations, and discovered spatial spillover effects from both the decomposition (spatial shift-share) and modelling approach. The presence of positive spatial spillover effects suggests that a destination can benefit from the presence of highly attractive destinations in the neighbourhood, and not only from its own endowment of tourism resources. This result emerged from the explanatory analysis carried out in the second chapter, and is confirmed by the econometric analysis performed in Chapter 3. However, it is also true that a badly performing neighbour may even reduce the attractiveness of a destination with great tourist potential. If destination managers ignore this, the attractiveness of the entire territory may be negatively affected. Furthermore, the attractiveness of Italian destinations may also be weakened by external shocks, like the Great recession, and their ability to resist and respond will also depend on their structural characteristics and tourist vocation.

The empirical evidence that emerged from this thesis may be useful for practitioners and Destination Management Organisations (DMOs) aiming to enhance destination attractiveness. They will, for example, need to cooperate with each other and with policy makers to develop coordinated actions to exploit the presence of spatial spillover effects, which may improve the attractiveness and profitability of the entire territory. They will also need to support local tourism and reduce disparities among destinations, in order to prevent a weakening of the entire Italian brand because unattractive neighbours may reduce the performance of destinations with a great tourist potential. Furthermore, Destination Management Organisations and policy makers need to develop policies that reduce the vulnerability of destinations and improve their ability to respond to crisis shocks. Cooperation amongst institutions at all administrative levels is obviously a key factor in the success of this great enterprise.

Bibliography

Alavi, J. and Yasin, M. M. (2000). A systematic approach to tourism policy. *Journal of Business Research*, 48(2):147–156.

Alvarez-Diaz, M., D'Hombres, B., and Ghisetti, C. (2017). Modelling inter- and intraregional tourism flows in Spain – a spatial econometric approach. *Regional Statistics*, 7(2):3–34. doi: https://doi.org/10.15196/RS070205.

Alvarez-Diaz, M., D'Hombres, B., Ghisetti, C., and Pontarollo, N. (2020). Analysing domestic tourism flows at the provincial level in Spain by using spatial gravity models. *International Journal of Tourism Research*, 22(4):403–415. doi: https://doi.org/10.1016/10.1002/jtr.2344.

Araña, J. E. and León, C. J. (2008). The impact of terrorism on tourism demand. *Annals of Tourism Research*, 35(2):299–315. doi: https://doi.org/10.1016/j.annals.2007.08.003.

Au, A. K. M., Ramasamy, B., and Yeung, M. C. H. (2005). The effects of SARS on the Hong Kong tourism industry: An empirical evaluation. *Asia Pacific Journal of Tourism Research*, 10(1):85–95. doi: https://doi.org/10.1080/1094166042000330236.

Bailey, N., Holly, S., and Pesaran, M. H. (2016a). A Two-Stage Approach to Spatio-Temporal Analysis with Strong and Weak Cross-Sectional Dependence. *Journal of Applied Econometrics*, 31(1):249–280. doi: https://doi.org/10.1002/jae.2468.

Bailey, N., Kapetanios, G., and Pesaran, M. H. (2016b). Exponent of Cross-Sectional Dependence: Estimation and Inference. *Journal of Applied Econometrics*, 31(6):929–960. doi: https://doi.org/10.1002/jae.2476.

Barcaccia, G., D'Agostino, V., Zotti, A., and Cozzi, B. (2020). Impact of the SARS-CoV-2 on the Italian Agri-Food Sector: An Analysis of the Quarter of Pandemic Lockdown and Clues for a Socio-Economic and Territorial Restart. *Sustainability*, 12(14). doi: https://doi.org/10.3390/su12145651.

Barff, R. A. and Knight III, P. L. (1988). Dynamic shift-share analysis. *Growth and Change*, 19(2):1–10. doi: 10.1111/j.1468-2257.1988.tb00465.x.

Barman, H. and Nath, H. K. (2019). What determines international tourist arrivals in India? *Asia Pacific Journal of Tourism Research*, 24(2):180–190. doi: https://doi.org/10.1080/10941665.2018.1556712.

Bassil, C., Saleh, A. S., and Anwar, S. (2019). Terrorism and tourism demand: a case study of Lebanon, Turkey and Israel. *Current Issues in Tourism*, 22(1):50–70. doi: https://doi.org/10.1080/13683500.2017.1397609.

Bernini, C., Cracolici, M. F., and Nijkamp, P. (2020). Micro and Macro Resilience Measures of an Economic Crisis. *Networks and Spatial Economics*, 20(1):47–71. doi: https://doi.org/10.1007/s11067-019-09470-9.

Berzeg, K. (1978). The empirical content of shift-share analysis. *Journal of Regional Science*, 18(3):463–468. doi: 10.1111/j.1467-9787.1978.tb00563.x.

Bhamra, R., Dani, S., and Burnard, K. (2011). Resilience: the concept, a literature review and future directions. *International Journal of Production Research*, 49(18):5375–5393. doi: https://doi.org/10.1080/00207543.2011.563826.

Bianchi, A. and Biffignandi, S. (2018). Employment growth by firm size during the recent crisis in Italy: a multifactor partitioning analysis. *Growth and Change*, 49(2):314–338.

Bo, Z., Bi, Y., Hengyun, L., and Hailin, Q. (2017). The spillover effect of attractions: Evidence from Eastern China. *Tourism Economics*, 23(4):731–743. doi: https://doi.org/10.5367/te.2016.0541.

Brida, J. G. and Risso, W. A. (2009). A Dynamic Panel Data Study of the German Demand for Tourism in South Tyrol. *Tourism and Hospitality Research*, 9(4):305–313. doi: https://doi.org/10.1057/thr.2009.15.

Broekel, T. and Alfken, C. (2015). Gone with the wind? The impact of wind turbines on tourism demand. *Energy Policy*, 86:506–519. doi: https://doi.org/10.1016/j.enpol.2015.08.005.

Cafiso, G., Cellini, R., and Cuccia, T. (2018). Do economic crises lead tourists to closer destinations? Italy at the time of the Great Recession. *Papers in Regional Science*, 97(2):369–386. doi: https://doi.org/10.1111/pirs.12242.

Cellini, R. and Cuccia, T. (2015). The economic resilience of tourism industry in Italy: What the 'great recession' data show. *Tourism Management Perspectives*, 16:346–356. doi: https://doi.org/10.1016/j.tmp.2015.09.007.

Cellini, R. and Cuccia, T. (2019). Do behaviours in cultural markets affect economic resilience? An analysis of Italian regions. *European Planning Studies*, 27(4):784–801.

Chasapopoulos, P., Butter, F. A. D., and Mihaylov, E. (2014). Demand for tourism in Greece: a panel data analysis using the gravity model. *International Journal of Tourism Policy*, 5(3):173–191. doi: https://doi.org/10.1504/IJTP.2014.063105.

Chen, Z. and Haynes, K. E. (2015). Impact of high-speed rail on international tourism demand in China. *Applied Economics Letters*, 22(1):57–60. doi: https://doi.org/10.1080/13504851.2014.925043.

Cheng, S. (2011). Business cycle, industrial composition, or regional advantage? A decomposition analysis of new firm formation in the United States. *The Annals of Regional Science*, 47:147–167.

Chou, M. C. (2013). Does tourism development promote economic growth in transition countries? A panel data analysis. *Economic Modelling*, 33:226–232. doi: https://doi.org/10.1016/j.econmod.2013.04.024.

Chudik, A., Pesaran, M. H., and Tosetti, E. (2011). Weak and strong cross-section dependence and estimation of large panels. *The Econometrics Journal*, 14(1):C45–C90. doi: https://doi.org/10.1111/j.1368-423X.2010.00330.x.

Ciccarelli, C. and Elhorst, J. (2018). A dynamic spatial econometric diffusion model with common factors: The rise and spread of cigarette consumption in Italy. *Regional Science and Urban Economics*, 72:131–142. doi: https://doi.org/10.1016/j.regsciurbeco.2017.07.003.

Corrado, L. and Fingleton, B. (2012). WHERE IS THE ECONOMICS IN SPATIAL ECONOMETRICS? *Journal of Regional Science*, 52(2):210–239. doi: https://doi.org/10.1111/j.1467-9787.2011.00726.x.

Costantino, S., Cracolici, M. F., and Piacentino, D. (2020). A New Spatial Shift-Share Decomposition: An Application to Tourism Competitiveness in Italian Regions. *Geographical Analysis*. doi: https://doi.org/10.1111/gean.12262.

Cracolici, M. F. and Nijkamp, P. (2006). Competition among tourist destination: an application of data envelopment analysis to Italian provinces. In Giaoutzi, M. and Nijkamp, P., editors, *Tourism and Regional Development. New Pathways*, pages 133–152. Aldershot. England: Ashgate.

Cracolici, M. F. and Nijkamp, P. (2008). The attractiveness and competitiveness of tourist destinations: a study of Southern Italian regions. *Tourism Management*, 30:336–344.

Cracolici, M. F., Nijkamp, P., and Rietveld, P. (2008). Assessment of tourism competitiveness by analysing destination efficiency. *Tourism Economics*, 14(2):325–342.

Crouch, G. I. and Ritchie, J. (1999). Tourism, Competitiveness, and Societal Prosperity. *Journal of Business Research*, 44(3):137–152. doi: https://doi.org/10.1016/S0148-2963(97)00196-3.

De la Mata, T. and Llano-Verduras, C. (2012). Spatial pattern and domestic tourism: An econometric analysis using inter-regional monetary flows by type of journey. *Papers in Regional Science*, 91(2):437–470. doi: 10.1111/j.1435-5957.2011.00376.x.

De Vita, G. and Kyaw, K. S. (2017). Tourism Specialization, Absorptive Capacity, and Economic Growth. *Journal of Travel Research*, 56(4):423–435. doi: https://doi.org/10.1177/0047287516650042.

Deluna, R. and Jeon, N. (2014). Determinants of international tourism demand for the Philippines: an augmented gravity model approach. Available at: https://mpra.ub.uni-muenchen.de/55294/ (accessed June 2020).

Deng, M. and Athanasopoulos, G. (2011). Modelling Australian domestic and international inbound travel: a spatial–temporal approach. *Tourism Management*, 32(5):1075–1084. doi: https://doi.org/10.1016/j.tourman.2010.09.006.

Deng, T. and Hu, Y. (2019). Modelling China's outbound tourist flow to the 'Silk Road': A spatial econometric approach. *Tourism Economics*, 25(8):1167–1181. doi: https://doi.org/10.1177/1354816618809763.

Di Berardino, C., Mauro, G., Quaglione, D., and Sarra, A. (2016). Structural change and the sustainability of regional convergence: Evidence from the italian regions. *Environment and Planning C: Politics and Space*, 35(2):289–311. doi: 10.1177/0263774X16655800.

Dogru, T. and Sirakaya, E. (2017). Engines of tourism's growth: An examination of efficacy of shift-share regression analysis in South Carolina. *Tourism Management*, 58:205–214.

Dogru, T., Suess, C., and Sirakaya-Turk, E. (2020). Why Do Some Countries Prosper than Others? Global Competitivenss of Tourism Development. *Journal of Hospitality and Tourism Research*, 20(10):1–42. doi: 10.1177/1096348020911706.

Dong, D., Xu, X., Yu, H., and Zhao, Y. (2019). The Impact of Air Pollution on Domestic Tourism in China: A Spatial Econometric Analysis. *Sustainability*, 11(15). doi: https://doi.org/10.3390/su11154148.

Doran, J. and Fingleton, B. (2014). Economic shocks and growth: Spatio-temporal perspectives on Europe's economies in a time of crisis. *Papers in Regional Science*, 93(S1):S137–S165. doi: https://doi.org/10.1111/pirs.12048.

Doran, J. and Fingleton, B. (2015). Resilience from the micro perspective. *Cambridge Journal of Regions, Economy and Society*, 8(2):205–223. doi: https://doi.org/10.1093/cjres/rsv004.

Doran, J. and Fingleton, B. (2018). US Metropolitan Area Resilience: Insights from dynamic spatial panel estimation. *Environment and Planning A: Economy and Space*, 50(1):111–132. doi: https://doi.org/10.1177/0308518X17736067.

Dunn, E. S. (1960). A statistical and analytical technique for regional analysis. *Papers of the Regional Science Association*, 6:97–112.

Elhorst, J. P. (2010). Applied Spatial Econometrics: Raising the Bar. *Spatial Economic Analysis*, 5(1):9–28. doi: https://doi.org/10.1080/17421770903541772.

Elhorst, J. P. (2014). *Spatial econometrics: from cross-sectional data to spatial panels*. Springer-Verlag, Berlin, Heidelberg. doi: https://doi.org/10.1007/978-3-642-40340-8.

Elhorst, J. P., Gross, M., and Tereanu, E. (2018). Spillovers in Space and Time: Where Spatial Econometrics and Global VAR Models Meet. *ECB Working Paper*, (2134). ISBN: 978-92-899-3239-4, Available at SSRN: https://ssrn.com/abstract=3134525.

Elhorst, J. P., Madre, J.-L., and Pirotte, A. (2020). Car traffic, habit persistence, cross-sectional dependence, and spatial heterogeneity: New insights using French departmental data. *Transportation Research Part A: Policy and Practice*, 132:614–632. doi: https://doi.org/10.1016/j.tra.2019.11.016.

Elhorst, P. and Halleck Vega, S. (2013). On spatial econometric models, spillover effects, and W. 53rd Congress of the European Regional Science Association: "Regional Integration: Europe, the Mediterranean and the World Economy", 27-31 August 2013, Palermo, Italy. European Regional Science Association (ERSA), Louvain-la-Neuve. Available at: http://hdl.handle.net/10419/123888.

Emmerson, R., Ramanathan, R., and Ramm, W. (1975). On the analysis of regional growth patterns. *Journal of Regional Science*, 15(1):17–28. doi: https://doi.org/10.1111/j.1467-9787.1975.tb01128.x.

Ertur, C. and Musolesi, A. (2017). Weak and Strong Cross-Sectional Dependence: A Panel Data Analysis of International Technology Diffusion. *Journal of Applied Econometrics*, 32(3):477–503. doi: https://doi.org/10.1002/jae.2538.

Espa, G., Filipponi, D., Giuliani, D., and Piacentino, D. (2014). Decomposing regional business change at plant level in Italy: a novel spatial shift-share approach. *Papers in Regional Science*, 93(1):113–136.

Esteban, J. (2000). Regional convergence in Europe and the industry mix: a shift-share analysis. *Regional Science and Urban Economics*, 30:353–364.

Esteban-Marquillas, J. (1972). Shift and Share analysis revisited. *Regional and Urban Economics*, 2(3):249–261.

EUROSTAT (2009). The impact of the crisis on employment. *EUROSTAT Statistics in focus*, https://op.europa.eu/en/publication-detail/-/publication/c9138020-a7c1-4cb8-a378-e57724dc1860/language-en/format-PDF/source-182580854.

EUROSTAT (2010). Tourism in Europe in 2009. *EUROSTAT Data in focus*, https://ec.europa.eu/eurostat/en/web/products-data-in-focus/-/ks-qa-10-024.

Ezcurra, R. and Pascual, P. (2007). Spatial disparities in productivity in Central and Eastern Europe. *Eastern European Economics*, 45(3):5–32.

Faggian, A., Gemmiti, R., Jaquet, T., and Santini, I. (2018). Regional economic resilience: the experience of the Italian local labor systems. *The Annals of Regional Science*, 60(2):393–410. doi: https://doi.org/10.1007/s00168-017-0822-9.

Fazio, G. and Piacentino, D. (2010). A Spatial Multilevel Analysis of Italian SMEs' Productivity. *Spatial Economic Analysis*, 5(3):299–316. doi: 10.1080/17421772.2010.493953.

Fingleton, B., Garretsen, H., and Martin, R. (2012). RECESSIONARY SHOCKS AND REGIONAL EMPLOYMENT: EVIDENCE ON THE RESILIENCE OF U.K. REGIONS. *Journal of Regional Science*, 52(1):109–133. doi: https://doi.org/10.1111/j.1467-9787.2011.00755.x.

Fingleton, B., Garretsen, H., and Martin, R. (2015). Shocking aspects of monetary union: the vulnerability of regions in Euroland. *Journal of Economic Geography*, 15(5):907–934. doi: https://doi.org/10.1093/jeg/lbu055.

Fingleton, B. and Palombi, S. (2013). Spatial panel data estimation, counterfactual predictions, and local economic resilience among British towns in the Victorian era. *Regional Science and Urban Economics*, 43(4):649–660. doi: https://doi.org/10.1016/j.regsciurbeco.2013.04.005.

Firgo, M. and Fritz, O. (2017). Does having the right visitor mix do the job? Applying an econometric shift-share model to regional tourism developments. *The Annals of Regional Science*, 58(3):469–490.

Franklin, R. and Plane, D. A. (2004). A shift-share method for the analysis of regional fertility change: An application to the decline in childbearing in italy, 1952–1991. *Geographical Analysis*, 36(1):1–20. doi: 10.1111/j.1538-4632.2004.tb01120.x.

Fuchs, M., Rijken, L., Peters, M., and Weiermair, K. (2000). Modelling Asian incoming tourism: a shift-share approach. *Asia Pacific Journal of Tourism Research*, 5:1–10.

Gardini, A. (1979). Un'analisi interregionale dei flussi turistici e dei coefficienti gravitazionali di Leontief-Strout relativi al turismo interno. *Statistica*, 39(3):455–478.

Garín Muñoz, T. (2006). Inbound international tourism to Canary Islands: a dynamic panel data model. *Tourism Management*, 27(2):281–291. doi: https://doi.org/10.1016/j.tourman.2004.10.002.

Garín Muñoz, T. (2007). German demand for tourism in Spain. *Tourism Management*, 28(1):12–22. doi: https://doi.org/10.1016/j.tourman.2005.07.020.

Giannakis, E. and Bruggeman, A. (2017). Economic crisis and regional resilience: Evidence from Greece. *Papers in Regional Science*, 96(3):451–476. doi: https://doi.org/10.1111/pirs.12206.

Goh, C. (2012). Exploring impact of climate on tourism demand. *Annals of Tourism Research*, 39(4):1859–1883. doi: https://doi.org/10.1016/j.annals.2012.05.027.

Grossi, L. and Mussini, M. (2018). A spatial shift-share decomposition of electricity consumption changes across Italian regions. *Energy Policy*, 113:278–293.

Gössling, S., Scott, D., and Hall, C. M. (2021). Pandemics, tourism and global change: a rapid assessment of COVID-19. *Journal of Sustainable Tourism*, 29(1):1–20. doi: https://doi.org/10.1080/09669582.2020.1758708.

Gunter, U., Önder, I., and Zekan, B. (2020). Modeling Airbnb demand to New York City while employing spatial panel data at the listing level. *Tourism Management*, 77. doi: https://doi.org/10.1016/j.tourman.2019.104000.

Habibi, F. (2017). The determinants of inbound tourism to Malaysia: a panel data analysis. *Current Issues in Tourism*, 20(9):909–930. doi: https://doi.org/10.1080/13683500.2016.1145630.

Habibi, F., Rahim, K. A., Ramchandran, S., and Chin, L. (2009). Dynamic model for international tourism demand for Malaysia: Panel data evidence. *International Research Journal of Finance and Economics*, 33(1):208–217.

Halleck Vega, S. and Elhorst, J. P. (2015). THE SLX MODEL. *Journal of Regional Science*, 55(3):339–363. doi: https://doi.org/10.1111/jors.12188.

Halleck Vega, S. and Elhorst, J. P. (2016). A regional unemployment model simultaneously accounting for serial dynamics, spatial dependence and common factors. *Regional Science and Urban Economics*, 60:85–95. doi: https://doi.org/10.1016/j.regsciurbeco.2016.07.002.

Haque, T. H. and Haque, M. O. (2018). Evaluating the Impacts of the Global Financial Crisis on Tourism in Brunei. *Tourism Analysis*, 23:409–414. doi: https://doi.org/10.3727/108354218X15305418667011.

Harb, G. and Bassil, C. (2020). Gravity analysis of tourism flows and the 'multilateral resistance to tourism'. *Current Issues in Tourism*, 23(6):666–678. doi: https://doi.org/10.1080/13683500.2018.1544612.

Haynes, K. E. and Machunda, Z. B. (1988). Decomposition of change in spatial employment concentration: An information-theoretic extension of shift-share analysis. *Papers in Regional Science*, 65(1):101–113.

Holling, C. S. (1973). Resilience and Stability of Ecological Systems. *Annual Review of Ecology and Systematics*, 4(1):1–23. doi: https://doi.org/10.1146/annurev.es.04.110173.000245.

Hudec, O., Reggiani, A., and Šiserová, M. (2018). Resilience capacity and vulnerability: A joint analysis with reference to Slovak urban districts. *Cities*, 73:24–35. doi: https://doi.org/10.1016/j.cities.2017.10.004.

ISTAT (2012). The first Italian tourism satellite account. https://www.istat.it/it/files//2018/01/EN_Tourism-satellite-account.pdf.

ISTAT (2017). The Italian tourism satellite account. http://www.istat.it/en/archive/71012.

ISTAT (2020a). Classificazione dei Comuni in base alla Densità Turistica. https://www.istat.it/it/archivio/247191.

ISTAT (2020b). Conto Satellite del Turismo per l'Italia. https://www.istat.it/it/files//2020/06/Conto-satellite-turismo.pdf.

Jacobsen, J. K. S. and Munar, A. M. (2012). Tourist information search and destination choice in a digital age. *Tourism Management Perspectives*, 1:39–47. doi: https://doi.org/10.1016/j.tmp.2011.12.005.

Jiao, X., Li, G., and Chen, J. L. (2020). Forecasting international tourism demand: a local spatiotemporal model. *Annals of Tourism Research*, 83. doi: https://doi.org/10.1016/j.annals.2020.102937.

Khadaroo, J. and Seetanah, B. (2008). The role of transport infrastructure in international tourism development: A gravity model approach. *Tourism Management*, 29(5):831–840. doi: https://doi.org/10.1016/j.tourman.2007.09.005.

Kitsos, A. and Bishop, P. (2018). Economic resilience in Great Britain: the crisis impact and its determining factors for local authority districts. *Annals of Regional Science*, 60(2):329–347. doi: https://doi.org/10.1007/s00168-016-0797-y.

Kožić, I. (2014). Detecting international tourism demand growth cycles. *Current Issues in Tourism*, 17(5):397–403. doi: https://doi.org/10.1080/13683500.2013.808607.

Kuo, H.-I., Chen, C.-C., Tseng, W.-C., Ju, L.-F., and Huang, B.-W. (2008). Assessing impacts of SARS and Avian Flu on international tourism demand to Asia. *Tourism Management*, 29(5):917–928. doi: https://doi.org/10.1016/j.tourman.2007.10.006.

Kusni, A., Kadir, N., and Nayan, S. (2013). International Tourism Demand in Malaysia by Tourists from OECD Countries: A Panel Data Econometric Analysis. *Procedia Economics and Finance*, 7:28–34. International Conference on Economics and Business Research 2013 (ICEBR 2013). doi: https://doi.org/10.1016/S2212-5671(13)00214-1.

Lauridsen, J. (1999). Spatial cointegration analysis in econometric modelling. 39th Congress of the European Regional Science Association: "Regional Cohesion and Competitiveness in 21st Century Europe", August 23 - 27, 1999, Dublin, Ireland. European Regional Science Association (ERSA). Louvain-la-Neuve.

Le Gallo, J. and Kamarianakis, Y. (2011). The Evolution of Regional Productivity Disparities in the European Union from 1975 to 2002: A Combination of Shift–Share and Spatial Econometrics. *Regional Studies*, 45(1):123–139. doi: 10.1080/00343400903234662.

Le Sage, J. P. and Pace, R. K. (2008). Spatial econometric modeling of origin-destination flows. *Journal of Regional Science*, 48(5):941–967.

Le Sage, J. P. and Pace, R. K. (2009). *Introduction to Spatial Econometrics*. Chapman and Hall/CRC, Boca Raton, 1st edition edition. doi: https://doi.org/10.1201/9781420064254.

Ledesma-Rodríguez, F. J., Navarro-Ibáñez, M., and Pérez-Rodríguez, J. V. (2001). Panel Data and Tourism: A Case Study of Tenerife. *Tourism Economics*, 7(1):75–88. doi: https://doi.org/10.5367/000000001101297748.

Lee, L. F. and Yu, J. (2010). Some recent developments in spatial panel data models. *Regional Science and Urban Economics*, 40(5):255–271. Advances In Spatial Econometrics. doi: https://doi.org/10.1016/j.regsciurbeco.2009.09.002.

Li, G., Song, H., and Witt, S. F. (2005). Recent Developments in Econometric Modeling and Forecasting. *Journal of Travel Research*, 44(1):82–99. doi: https://doi.org/10.1177/0047287505276594.

Li, H., Song, H., and Li, L. (2017). A Dynamic Panel Data Analysis of Climate and Tourism Demand: Additional Evidence. *Journal of Travel Research*, 56(2):158–171. doi: https://doi.org/10.1177/0047287515626304.

Li, Z., Zhang, S., Liu, X., Kozak, M., and Wen, J. (2020). Seeing the invisible hand: Underlying effects of COVID-19 on tourists' behavioral patterns. *Journal of Destination Marketing & Management*, 18:100502. doi: https://doi.org/10.1016/j.jdmm.2020.100502.

Lim, C. and Zhu, L. (2017). Dynamic heterogeneous panel data analysis of tourism demand for Singapore. *Journal of Travel & Tourism Marketing*, 34(9):1224–1234. doi: https://doi.org/10.1080/10548408.2017.1330173.

Litman, J. (2005). Curiosity and the pleasures of learning: Wanting and liking new information. *Cognition and Emotion*, 19(6):793–814. doi: https://doi.org/10.1080/02699930541000101.

Liu, A. and Pratt, S. (2017). Tourism's vulnerability and resilience to terrorism. *Tourism Management*, 60:404–417. doi: https://doi.org/10.1016/j.tourman.2017.01.001.

Liu, T. M. (2020). Habit formation or word of mouth: What does lagged dependent variable in tourism demand models imply? *Tourism Economics*, 26(3):461–474. doi: https://doi.org/10.1177/1354816619843041.

Liu, Y., Li, Y., and Li, L. (2018). A panel data-based analysis of factors influencing market demand for Chinese outbound tourism. *Asia Pacific Journal of Tourism Research*, 23(7):667–676. doi: https://doi.org/10.1080/10941665.2018.1486863.

Maloney, W. F. and Montes Rojas, G. V. (2005). How elastic are sea, sand and sun? Dynamic panel estimates of the demand for tourism. *Applied Economics Letters*, 12(5):277–280. doi: https://doi.org/10.1080/1350485042000338626.

Marimon, R. and Zilibotti, F. (1998). 'Actual' versus 'virtual' employment in Europe Is Spain different? *European Economic Review*, 42(1):123–153.

Marrocu, E. and Paci, R. (2013). Different tourists to different destinations: evidence from spatial interaction models. *Tourism Management*, 39:71–83.

Martenson, R. (2018). Curiosity motivated vacation destination choice in a reward and variety-seeking perspective. *Journal of Retailing and Consumer Services*, 41:70–78. doi: https://doi.org/10.1016/j.jretconser.2017.11.009.

Martin, R. (2010). Roepke Lecture in Economic Geography—Rethinking Regional Path Dependence: Beyond Lock-in to Evolution. *Economic Geography*, 86(1):1–27. doi: https://doi.org/10.1111/j.1944-8287.2009.01056.x.

Martin, R. (2012). Regional economic resilience, hysteresis and recessionary shocks. *Journal of Economic Geography*, 12(1):1–32. doi: https://doi.org/10.1093/jeg/lbr019.

Martin, R. and Gardiner, B. (2019). The resilience of cities to economic shocks: A tale of four recessions (and the challenge of Brexit). *Papers in Regional Science*, 98(4):1801–1832. doi: https://doi.org/10.1111/pirs.12430.

Martin, R. and Sunley, P. (2015). On the notion of regional economic resilience: conceptualization and explanation. *Journal of Economic Geography*, 15(1):1–42. doi: https://doi.org/10.1093/jeg/lbu015.

Martin, R., Sunley, P., Gardiner, B., and Tyler, P. (2016). How Regions React to Recessions: Resilience and the Role of Economic Structure. *Regional Studies*, 50(4):561–585. doi: https://doi.org/10.1080/00343404.2015.1136410.

Massidda, C. and Etzo, I. (2012). The determinants of Italian domestic tourism: A panel data analysis. *Tourism Management*, 33(3):603–610. doi: https://doi.org/10.1016/j.tourman.2011.06.017.

Mayor, F. M. and López, M. A. J. (2008). Spatial shift-share analysis versus spatial filtering: an application to Spanish employment data. *Empirical Economics*, 34:123–142.

Modica, M. and Reggiani, A. (2015). Spatial Economic Resilience: Overview and Perspectives. *Networks and Spatial Economics*, 15(2):211–233. doi: https://doi.org/10.1007/s11067-014-9261-7.

Modica, M., Reggiani, A., and Nijkamp, P. (2019). Vulnerability, Resilience and Exposure: Methodological Aspects. In Okuyama, Y. and Rose, A., editors, *Advances in Spatial and Economic Modeling of Disaster Impacts*, pages 295–324. Springer International Publishing, Cham. doi: https://doi.org/10.1007/978-3-030-16237-5_12.

Moran, P. A. (1950). Notes on continous stochastic phenomena. *Biometrika*, 37:17–23.

Morley, C., Rosselló, J., and Santana-Gallego, M. (2014). Gravity models for tourism demand: theory and use. *Annals of Tourism Research*, 48:1–10. doi: https://doi.org/10.1016/j.annals.2014.05.008.

Morley, C. L. (1998). A dynamic international demand model. *Annals of Tourism Research*, 25(1):70–84. doi: https://doi.org/10.1016/S0160-7383(97)00067-4.

Muryani, M., Permatasari, M. F., and Padilla, M. A. E. (2020). DETERMINANTS OF TOURISM DEMAND IN INDONESIA: A PANEL DATA ANALYSIS. *Tourism Analysis*, 25:77–89. doi: https://doi.org/10.3727/108354220X15758301241666.

Mussini, M. (2018). A spatial decomposition of the shift-share components of labour productivity inequality in Italy. *Papers in Regional Science*, DOI: 10.1111/pirs.12362.

Nazara, S. and Hewings, G. J. D. (2004). Spatial structure and taxonomy of decomposition in shift–share analysis. *Growth and Change*, 35:476–490.

OECD (2011). OECD studies on tourism: Italy. doi: http://dx.doi.org/10.1787/9789264114258-en.

Okumus, F., Altinay, M., and Arasli, H. (2005). The impact of Turkey's economic crisis of February 2001 on the tourism industry in Northern Cyprus. *Tourism Management*, 26(1):95–104. doi: https://doi.org/10.1016/j.tourman.2003.08.013.

Parent, O. and Le Sage, J. P. (2011). A space–time filter for panel data models containing random effects. *Computational Statistics & Data Analysis*, 55(1):475–490. doi: https://doi.org/10.1016/j.csda.2010.05.016.

Parent, O. and Le Sage, J. P. (2012). Spatial dynamic panel data models with random effects. *Regional Science and Urban Economics*, 42(4):727–738. doi: https://doi.org/10.1016/j.regsciurbeco.2012.04.008.

Park, J.-Y. and Jang, S. S. (2014). An Extended Gravity Model: Applying Destination Competitiveness. *Journal of Travel & Tourism Marketing*, 31(7):799–816. doi: https://doi.org/10.1080/10548408.2014.889640.

Patuelli, R., Mussoni, M., and Candela, G. (2013). The effects of World Heritage Sites on domestic tourism: a spatial interaction model for Italy. *Journal of Geographical Systems*, 15:369–402. doi: https://doi.org/10.1007/s10109-013-0184-5.

Patuelli, R., Mussoni, M., and Candela, G. (2014). Cultural offer and distance in a spatial interaction model for tourism. *Economics and Business Letters*, 3(2):96–108.

Perles-Ribes, J. F., Ramón-Rodríguez, A. B., Sevilla-Jiménez, M., and Rubia, A. (2016). The Effects of Economic Crises on Tourism Success: An Integrated Model. *Tourism Economics*, 22(2):417–447. doi: https://doi.org/10.5367/te.2014.0428.

Pesaran, M. H. (2006). Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure. *Econometrica*, 74(4):967–1012. doi: https://doi.org/10.1111/j.1468-0262.2006.00692.x.

Pesaran, M. H. (2015). Testing Weak Cross-Sectional Dependence in Large Panels. *Econometric Reviews*, 34(6-10):1089–1117. doi: https://doi.org/10.1080/07474938.2014.956623.

Pesaran, M. H., Smith, L. V., and Yamagata, T. (2013). Panel unit root tests in the presence of a multifactor error structure. *Journal of Econometrics*, 175(2):94–115. doi: https://doi.org/10.1016/j.jeconom.2013.02.001.

Piacentino, D., Bono, F., Cracolici, M. F., and Giuliani, D. (2017a). A spatial analysis of new business formation: Replicative vs innovative behaviour. *Spatial Statistics*, 21:390–405. Regional Economy and Development: A Viewpoint and Application of Spatial Statistics. doi: https://doi.org/10.1016/j.spasta.2017.02.004.

Piacentino, D., Espa, G., Filipponi, D., and Giuliani, D. (2017b). Firm demography and regional development. Evidence from Italy. *Growth and Change*, 48(3):359–389.

Pinkse, J. and Slade, M. E. (2010). THE FUTURE OF SPATIAL ECONOMETRICS. *Journal of Regional Science*, 50(1):103–117. doi: https://doi.org/10.1111/j.1467-9787.2009.00645.x.

Plane, D. A. (1987). The geographic components of change in a migration system. *Geographical Analysis*, 19(4):283–299. doi: 10.1111/j.1538-4632.1987.tb00131.x.

Plane, D. A. (1992). Age-composition change and the geographical dynamics of interregional migration in the u.s. *Annals of the Association of American Geographers*, 82(1):64–85. doi: 10.1111/j.1467-8306.1992.tb01898.x.

Polyzos, S., Samitas, A., and Spyridou, A. E. (2020). Tourism demand and the COVID-19 pandemic: an LSTM approach. *Tourism Recreation Research*. doi: 10.1080/02508281.2020.1777053.

Pompili, T., Pisati, M., and Lorenzini, E. (2019). Determinants of international tourist choices in Italian provinces: A joint demand–supply approach with spatial effects. *Papers in Regional Science*, 98(6):2251–2273. doi: https://doi.org/10.1111/pirs.12467.

Porto, N., Garbero, N., and Espinola, N. (2018). Spatial distribution of touristic flows in a gravity model in South America. *Journal of Tourism Analysis: Revista de Análisis Turístico*, 25(1):39–53. doi: https://doi.org/10.1108/JTA-02-2018-0005.

Prideaux, B. and Witt, S. F. (2000). The impact of the Asian financial crisis on Australian tourism. *Asia Pacific Journal of Tourism Research*, 5(1):1–7. doi: https://doi.org/10.1080/10941660008722053.

Reid, R. and Botterill, L. C. (2013). The Multiple Meanings of 'Resilience': An Overview of the Literature. *Australian Journal of Public Administration*, 72(1):31–40. doi: https://doi.org/10.1111/1467-8500.12009.

Ritchie, J. R. B., Molinar, C. M. A., and Frechtling, D. C. (2010). Impacts of the World Recession and Economic Crisis on Tourism: North America. *Journal of Travel Research*, 49(1):5–15. doi: https://doi.org/10.1177/0047287509353193.

Rodríguez, X. A., Martínez-Roget, F., and Pawlowska, E. (2012). Academic tourism demand in Galicia, Spain. *Tourism Management*, 33(6):1583–1590. doi: https://doi.org/10.1016/j.tourman.2012.01.010.

Romão, J. and Saito, H. (2017). A spatial analysis on the determinants of tourism performance in Japanese Prefectures. *Asia-Pacific Journal of Regional Science*, 1:243–264.

Romer, R. (2001). *Advanced Macroeconomics*. McGraw Hill, New York.

Romão, J. (2015). Culture or Nature: a space-time analysis on the determinants of tourism demand in European regions. Discussion Papers Spatial and Organisational Dynamics 14.

Romão, J. and Nijkamp, P. (2018). Spatial impacts assessment of tourism and territorial capital: A modelling study on regional development in Europe. *International Journal of Tourism Research*, 20(6):819–829. doi: https://doi.org/10.1002/jtr.2234.

Rosenfeld, F. (1959). Commentaire à l'exposé de M. Dunn. *Economic Appliquée*, 4:531–534.

Rosselló, J., Becken, S., and Santana-Gallego, M. (2020). The effects of natural disasters on international tourism: A global analysis. *Tourism Management*, 79. doi: https://doi.org/10.1016/j.tourman.2020.104080.

Rosselló-Nadal, J. (2014). How to evaluate the effects of climate change on tourism. *Tourism Management*, 42:334–340. doi: https://doi.org/10.1016/j.tourman.2013.11.006.

Sakashita, N. (1973). An axiomatic approach to shift-and-share analysis. *Regional and Urban Economics*, 3(3):263 – 272. doi: https://doi.org/10.1016/0034-3331(73)90012-2.

Samitas, A., Asteriou, D., Polyzos, S., and Kenourgios, D. (2018). Terrorist incidents and tourism demand: Evidence from Greece. *Tourism Management Perspectives*, 25:23–28. doi: https://doi.org/10.1016/j.tmp.2017.10.005.

Santeramo, F. G. and Morelli, M. (2016). Modelling tourism flows through gravity models: a quantile regression approach. *Current Issues in Tourism*, 19(11):1077–1083. doi: https://doi.org/10.1080/13683500.2015.1051518.

Sequeira, T. N. and Nunes, P. M. (2008). Does tourism influence economic growth? A dynamic panel data approach. *Applied Economics*, 40(18):2431–2441. doi: https://doi.org/10.1080/00036840600949520.

Silva, J. M. C. S. and Tenreyro, S. (2006). The Log of Gravity. *The Review of Economics and Statistics*, 88(4):641–658.

Simmie, J. and Martin, R. (2010). The economic resilience of regions: towards an evolutionary approach. *Cambridge Journal of Regions, Economy and Society*, 3(1):27–43. doi: https://doi.org/10.1093/cjres/rsp029.

Sirakaya, E., Choi, H. S., and Var, T. (2002). Shift-share analysis in tourism: examination of tourism development change in a region. *Tourism Economics*, 8:303–324.

Sirakaya, E., Uysal, M., and Toepper, L. (1995). Measuring the performance of South Carolina's tourist industry from shift-share analysis: A case study. *Journal of travel Research*, 1(2):55–62.

Smeral, E. (2009). The impact of the financial and economic crisis on european tourism. *Journal of Travel Research*, 48(1):3–13. doi: https://doi.org/10.1177/0047287509336332.

Smeral, E. (2010). Impacts of the World Recession and Economic Crisis on Tourism: Forecasts and Potential Risks. *Journal of Travel Research*, 49(1):31–38. doi: https://doi.org/10.1177/0047287509353192.

Sánchez, A. G. and López, D. S. (2015). Tourism Destination Competitiveness: The Spanish Mediterranean Case. *Tourism Economics*, 21(6):1235–1254. doi: https://doi.org/10.5367/te.2014.0405.

Song, H., Dwyer, L., Li, G., and Cao, Z. (2012). Tourism economics research: A review and assessment. *Annals of Tourism Research*, 39(3):1653–1682. doi = https://doi.org/10.1016/j.annals.2012.05.023.

Song, H. and Li, G. (2008). Tourism demand modelling and forecasting—A review of recent research. *Tourism Management*, 29(2):203–220. doi: https://doi.org/10.1016/j.tourman.2007.07.016.

Song, H. and Lin, S. (2010). Impacts of the Financial and Economic Crisis on Tourism in Asia. *Journal of Travel Research*, 49(1):16–30. doi: https://doi.org/10.1177/0047287509353190.

Song, H., Lin, S., Zhang, X., and Gao, Z. (2010). Global Financial/Economic Crisis and Tourist Arrival Forecasts for Hong Kong. *Asia Pacific Journal of Tourism Research*, 15(2):223–242. doi: https://doi.org/10.1080/10941661003687431.

Song, H., Qiu, R. T., and Park, J. (2019). A review of research on tourism demand forecasting: Launching the Annals of Tourism Research Curated Collection on tourism demand forecasting. *Annals of Tourism Research*, 75:338–362. doi: https://doi.org/10.1016/j.annals.2018.12.001.

Östh, J., Reggiani, A., and Galiazzo, G. (2015). Spatial economic resilience and accessibility: A joint perspective. *Computers, Environment and Urban Systems*, 49:148–159. doi: https://doi.org/10.1016/j.compenvurbsys.2014.07.007.

Strobl, E., Ouattara, B., and Kablan, S. A. (2020). Impact of hurricanes strikes on international reserves in the Caribbean. *Applied Economics*, 52(38):4175–4185. doi: https://doi.org/10.1080/00036846.2020.1731411.

Tang, C. F. and Tan, E. C. (2016). The determinants of inbound tourism demand in Malaysia: another visit with non-stationary panel data approach. *Anatolia*, 27(2):189–200. doi: https://doi.org/10.1080/13032917.2015.1084345.

Tatoglu, F. Y. and Gul, H. (2019). Analysis of tourism demand using a multi-dimensional panel gravity model. *Tourism Review*, 75(2):433–447. doi: https://doi.org/10.1108/TR-05-2019-0147.

Theil, H. and Gosh, R. (1980). A comparison of shift-share and the RAS adjustment. *Regional Science and Urban Economics*, 10(2):175 – 180. doi: https://doi.org/10.1016/0166-0462(80)90024-1.

Tillé, Y., Dickson, M. M., Espa, G., and Giuliani, D. (2018). Measuring the spatial balance of a sample: A new measure based on Moran's I index. *Spatial Statistics*, 23:182–192. doi: https://doi.org/10.1016/j.spasta.2018.02.001.

Tinbergen, J. (1962). Shaping the world economy: suggestions for an international economic policy. *Twentieth Century Fund, New York*.

Toh, R. S., Khan, H., and Lim, L.-L. (2004). Two-Stage Shift-Share Analyses of Tourism Arrivals and Arrivals by Purpose of Visit: The Singapore Experience. *Journal of Travel Research*, 43(1):57–66. doi: https://doi.org/10.1177/0047287504265513.

Toulemonde, E. (2001). 'Actual' Versus 'Virtual' Employment in Belgium. *Regional Studies*, 35(6):513–518.

Tsai, C.-H. and Chen, C.-W. (2011). The establishment of a rapid natural disaster risk assessment model for the tourism industry. *Tourism Management*, 32(1):158–171. doi: https://doi.org/10.1016/j.tourman.2010.05.015.

Urso, G., Modica, M., and Faggian, A. (2019). Resilience and Sectoral Composition Change of Italian Inner Areas in Response to the Great Recession. *Sustainability*, 11(9). doi: https://doi.org/10.3390/su11092679.

Uğur, N. G. and Akbıyık, A. (2020). Impacts of COVID-19 on global tourism industry: A cross-regional comparison. *Tourism Management Perspectives*, 36:100744. doi: https://doi.org/10.1016/j.tmp.2020.100744.

Uysal, M. and Crompton, J. L. (1984). Determinants of demand for international tourist flows to Turkey. *Tourism Management*, 5(4):288–297. doi: https://doi.org/10.1016/0261-5177(84)90025-6.

Wang, Y.-S. (2009). The impact of crisis events and macroeconomic activity on Taiwan's international inbound tourism demand. *Tourism Management*, 30(1):75–82. doi: https://doi.org/10.1016/j.tourman.2008.04.010.

WEF (2017). The travel and tourism competitivenes report 2017. *World Economic Forum*.

Xu, D., Huang, Z., Hou, G., and Zhang, C. (2020). The spatial spillover effects of haze pollution on inbound tourism: evidence from mid-eastern China. *Tourism Geographies*, 22(1):83–104. doi: https://doi.org/10.1080/14616688.2019.1612464.

Xu, L., Wang, S., Li, J., Tang, L., and Shao, Y. (2019). Modelling international tourism flows to China: A panel data analysis with the gravity model. *Tourism Economics*, 25(7):1047–1069. doi: https://doi.org/10.1177/1354816618816167.

Yang, C.-H., Lin, H.-L., and Han, C.-C. (2010). Analysis of international tourist arrivals in China: The role of World Heritage Sites. *Tourism Management*, 31(6):827–837. doi: https://doi.org/10.1016/j.tourman.2009.08.008.

Yang, Y. and Fik, T. (2014). Spatial effects in regional tourism growth. *Annals of Tourism Research*, 46:144–162. doi: https://doi.org/10.1016/j.annals.2014.03.007.

Yang, Y. and Wong, K. K. (2013). Spatial distribution of tourist flows to China's cities. *Tourism Geographies*, 15(2):338–363.

Yang, Y. and Wong, K. K. F. (2012). A Spatial Econometric Approach to Model Spillover Effects in Tourism Flows. *Journal of Travel Research*, 51(6):768–778. doi: https://doi.org/10.1177/0047287512437855.

Yang, Y. and Zhang, H. (2019). Spatial-temporal forecasting of tourism demand. *Annals of Tourism Research*, 75:106–119. doi: https://doi.org/10.1016/j.annals.2018.12.024.

Yasin, M., Alavi, J., Sobral, F., and Lisboa, J. (2004). A shift-share analysis approach to understanding the dynamic of the Portuguese tourism market. *Journal of Travel & Tourism Marketing*, 17(4):11–22.

Yazdi, S. K. and Khanalizadeh, B. (2017). Tourism demand: a panel data approach. *Current Issues in Tourism*, 20(8):787–800. doi: https://doi.org/10.1080/13683500.2016.1170772.

Yu, J., de Jong, R., and Lee, L. F. (2008). Quasi-maximum likelihood estimators for spatial dynamic panel data with fixed effects when both n and T are large. *Journal of Econometrics*, 146(1):118–134. doi: https://doi.org/10.1016/j.jeconom.2008.08.002.

Yu, J., de Jong, R., and Lee, L. F. (2012). Estimation for spatial dynamic panel data with fixed effects: The case of spatial cointegration. *Journal of Econometrics*, 167(1):16–37. doi: https://doi.org/10.1016/j.jeconom.2011.05.014.

Yun, S. C. and Yang, Y. (2008). A Review of Shift-Share Analysis and Its Application in Tourism. *International Journal of Management Perspectives*, 1(1):21–30.

Yun, S. C., Zhang, J., Yang, Y., and Zhou, Z. (2007). Shift-share analysis on international tourism competitiveness – A case of Jiangsu province. *Chines Geographical Science*, 17(2):173–178.

Zhang, J. (2009). Spatial Distribution of Inbound Tourism in China: Determinants and Implications. *Tourism and Hospitality Research*, 9(1):32–49. doi: https://doi.org/10.1057/thr.2008.41.

Zhang, K., Hou, Y., and Li, G. (2020). Threat of infectious disease during an outbreak: Influence on tourists' emotional responses to disadvantaged price inequality. *Annals of Tourism Research*, 84:102993. doi: https://doi.org/10.1016/j.annals.2020.102993.

Zuo, B. and Huang, S. S. (2020). A Structural Change and Productiivity Perspective of Tourism's Contribution to Economic Growth: The Case of Zhangjiajie in China. *Journal of Travel Research*, 59(3):465–479. doi: 10.1177/0047287519841720.