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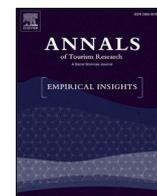
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# The interest in online museum experiences and the influence of uncertainty and sentiment factors on tourist arrivals: The case of EU Mediterranean countries

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## ABSTRACT

This study examines the determinants of tourist arrivals at hotels and short-stay accommodations for nine EU countries from January 2010 to March 2022. We identify four driving channels of foreign and domestic tourism flows: a traditional, a sentiment, a technological and a health channel. The latter comprises two novel variables: the museum search interest and the infectious disease equity market volatility tracker. The results reveal that traditional and new drivers related to market sentiments and interest in online tourism experiences affect arrivals. Notably, there is a substitution effect between online and in-presence tourism, and the larger the uncertainty, the more substantial the reduction in tourist arrivals. COVID-19 has affected especially Spain and Italy and more foreign than domestic tourists.

## 1. Introduction

The tourism sector is undergoing profound changes pushed by the COVID-19 pandemic and the advancement of information and communication technologies. Before the pandemic, tourism was one of the most vital sectors in the world economy: it contributed to >10% of the global GDP, represented 30% of services exports and created >330 million jobs, i.e. about 1 in 10 occupations worldwide (WTTC, 2022). While in 1950, 25 million people travelled abroad, by 2019, this value attained 1.5 billion travellers (IMF, 2020). The coronavirus pandemic, however, changed the global scenario. Travel restrictions, quarantines, and flight stops led to a 74% decline in international arrivals between January and March 2021, putting 100 million jobs at risk (UNWTO, 2022a).

Especially during the first pandemic wave, millions of people searched for cultural and travel experiences from their homes (UNWTO, 2022b). Consequently, the interest in virtual access to museums, heritage sites, theatres and cultural performances soared extraordinarily.

COVID-19 prompted museums and other cultural institutions to reorganise their strategies and define new virtual solutions to curtail physical interactions (UNESCO, 2021), such as virtual tours, online collections and exhibitions (WIPO, 2022).

In this new context, the present study explores the dynamics of tourism arrivals at different types of establishments and their determinants, distinguished into four channels reflecting traditional and new drivers. Besides traditional factors affecting tourism demand, such as income, prices and exchange rates (e.g. Rosselló Nadal & Santana-Gallego, 2022), we consider new factors that are changing tourist behaviour. They include the interest in virtual access to museums and psychological aspects. The existing studies underexplored these drivers; however, their inclusion is relevant for pinpointing the mechanisms facilitating tourist flows between countries, identifying new challenges coming from the new technologies and the health crisis and for helping policymakers and the tourism industry design strategies to sustain the tourism sector and improve its competitiveness.

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We focus on nine Mediterranean EU countries: Croatia, Cyprus, France, Greece, Italy, Malta, Portugal,<sup>1</sup> Slovenia and Spain, for the period 2010–2022. These countries are interesting to investigate since they are top tourist destinations.<sup>2</sup> Their varied natural landscapes, cultural attractions, art cities, archaeological endowments and gastronomy entice millions of visitors every year. For instance, Italy and Greece have a well-renowned historical heritage linked to the Roman and Hellenistic cultures (Algieri & Álvarez, 2022; Algieri, Aquino, & Succurro, 2016). France is popular for its architectural endowment, famous sights, and a reputed wine-making heritage (Fountain, Charters, & Laurence, 2021).

This study contributes to the extant literature in several ways. First, it examines the determinants of tourist arrivals from a broader perspective. In particular, we identify a traditional macroeconomic, a technological, an uncertainty-sentiment, and a health channel. The technological channel includes a variable measuring the potential access to virtual cultural sites and its impact on tourism flows and destination competitiveness. The influence of information search patterns in determining tourism demand has not yet been explored in the literature. Still, data on information search behaviour are an essential research instrument that can identify tourist interests, needs and intentions. Similarly, the uncertainty-sentiment channel, consisting of i. the Economic Policy Uncertainty (*epu*), ii. the Infectious Disease Equity Market Volatility Tracker, and iii. Business Sentiment, has received scant attention in the literature. While *epu* has been considered by the tourism literature<sup>3</sup> starting from Baker, Bloom, and Davis (2016), the infectious disease tracker, – a health risk indicator proposed by Baker, Bloom, and Davis (2020) – is a novel variable not yet included in the estimation of tourism demand. Business confidence is also a sentiment variable underexplored in the literature (Gholipour & Foroughi, 2020). The distinction across traditional macroeconomic, psychological, technological and health channels is important to quantify the significance of each group of drivers for tourism demand and to single out the specific area of policy interventions to foster the tourism sector.

Second, the study extends the literature by accounting for a cross-country dimension in shaping tourist arrivals over time by distinguishing among types of arrivals (national and foreign tourists) and categories of establishments (hotels and short-stay accommodations). This perspective provides a comprehensive overview of the tourism accommodation industry in the EU for domestic and international visitors.

Third, we adopt two classes of models, Panel Poisson and Negative Binomial regressions, in addition to classical fixed and random-effects panel methods. These techniques are relatively new in the tourism demand literature and have been adopted by a few studies (Adeola, Boso, & Evans, 2017; Martins, Gan, & Ferreira-Lopes, 2017). The Panel Poisson and the Negative Binomial regressions are very useful in this context because the dependent variables, tourist arrivals, have a count nature, i. e. they are discrete variables consisting of non-negative integers.

The remainder of the study is organised as follows. Section 2 discusses the literature on the topic. Section 3 presents methods and data. Section 4 shows the empirical analysis. Section 5 concludes.

## 2. Literature review

Several studies have examined the relationship between tourism demand and macroeconomic factors, with prices and income

<sup>1</sup> Albeit Portugal has its coastline on the Atlantic Ocean, it is considered a Mediterranean country for its temperate climate, vegetation and cultural affinity with Southern Europeans (Britannica, 2022; UNWTO, 2021).

<sup>2</sup> In 2021, tourists mainly visited Europe (67.9%), the Americas (18.4%), Asia (4.6%) and Africa (18.9%). At a disaggregated level, Southern Mediterranean countries recorded the highest percentage share, with 31.1% arrivals (WTO, 2022).

<sup>3</sup> See Demir, Bilgin, Karabulut, & Doker, 2022; Kuok et al., 2022; Işık et al., 2020.

representing the two key drivers (Ghosh, 2022; Peng, Song, Crouch, & Witt, 2015). The coronavirus pandemic has strongly impacted the tourism sector, thus stimulating a broad wave of academic research.<sup>4</sup> Kocak, Okumus, and Altin (2022) and Esquivias, Sugiharti, Rohmawati, and Sethi (2021) have documented that COVID-19 has severely contracted the international tourist demand, revenues and employment. Sun, Li, Lenzen, Malik, and Pomponi (2022) argued that the global economic effect on the tourism industry has been more than eight times larger than the 2008 global financial crisis.

The literature has shown that tourism is a sector extremely vulnerable to crises, epidemics, security threats, climate change and natural or human-induced disasters (e.g. Gössling, Scott, & Hall, 2021; McKercher, 2021; Santana-Gallego, Fourie, & Rosselló, 2020). Lee, Olasehinde-Williams, and Akadiri (2021), and Dwyer, Forsyth, and Spurr (2006), for instance, reported that the SARS and other epidemic outbreaks negatively conditioned the behaviour of millions of travellers and damaged the international tourism demand for several months. Karabulut, Bilgin, Demir, and Doker (2020) documented that pandemics measured by the ‘Discussion about Pandemics Index’ negatively affected tourist arrivals for low-income economies from 1996 to 2018. Although the world experienced many acute epidemics and pandemics in the last forty years, none had the dramatic implications of COVID-19 (Gössling et al., 2021) with its likely long-term structural changes for the tourism industry (Altuntas & Gok, 2021; Kušcer, Eichelberger, & Peters, 2022).

The literature has further documented that recovery from a health crisis is often longer for tourism activities than for other businesses. This pattern is particularly true if the crisis hampers the image of a given destination (Mair, Ritchie, & Walters, 2016) and tourists perceive a lessened journey safety. With reference to COVID-19, Zhang, Song, Wen, et al. (2021) forecast that the recovery speed will vary across areas, with the fastest group represented by China, Taiwan and Thailand and the slowest group represented by Australia, France and the US. Liu, Vici, Ramos, et al. (2021) suggested that the speed and intensity of the recovery from coronavirus will be faster for those destinations depending on short-haul markets. Fotiadis, Polyzos, and Huan (2021) forecasted significant falls in tourist arrivals with long persistence. Mertzanis and Papastathopoulos (2021) proposed the epidemiological susceptibility risk index to predict tourist flows helpful in managing the epidemic’s effects, while Plzáková and Smeral (2022) identified a pessimistic, modest-optimistic and optimistic scenario for foreign travel in the Euro Area due to COVID-19.

Technology has been fundamental during the pandemic, affecting consumer behaviour and tourism resilience. However, its impact on tourism demand has been underinvestigated. Samaroudi, Rodriguez, and Perry (2020), for instance, examined the digitalisation strategies of heritage institutions in the UK and the US during the April–July 2020 lockdown and their initiatives to favour cultural access to a wider audience, including the more vulnerable. Fennell (2021) and Tan, Aziz, and Ahmad (2021) have highlighted how several cultural institutions started offering digital experiences and mixed-reality technologies across art collections to fulfil the request of people during the physical closures. All these authors argued that what has been introduced as temporary measures could become a new trend in the sector.

In light of the recent health and technological developments, it becomes interesting to include these new factors in tourism demand models to enrich the analysis and provide insights into tourists’ behaviour useful for managerial and policy strategies. We further consider a group of uncertainty-sentiment variables that could add further comprehension of the decision to select a different type of accommodation across Mediterranean countries.

Indeed, John Maynard Keynes (1936) emphasised the importance of sentiment, psychological and emotional factors in driving the market

<sup>4</sup> See Yang, Zhang, and Rickly (2021) for a review of research on COVID-19 and tourism.

and argued that uncertainty tends to govern economic behaviour and equity prices. However, the literature on tourism demand has considered sentiment factors only recently, starting with the study by Chen and Chiou-Wei (2009), followed by the analyses by Styliadis and Terzidou (2014), Dragouni, Filis, Gavrilidis, and Santamaria (2016) and Balli, Shahzad, and Uddin (2018), among the others. One of the main reasons for this scant attention to sentiment factors has been the lack of indicators to measure “psychological” influences. The first studies tried to seize sentiment using GARCH models that capture uncertainty from the variance equation of classical tourism demand (Chen & Chiou-Wei, 2009). After the introduction of the *e*<sub>*pu*</sub> index by Baker et al. (2016), more studies (Navarro-Chávez, Gómez, & Marín-Leyva, 2022; Hailemariam & Ivanovski, 2022; Kuok, Koo, and Lim (2022); İşık, Sirakaya-Turk, & Ongan, 2020) have added uncertainty among potential tourism demand determinants. Therefore, similarly to them, we include *e*<sub>*pu*</sub> to model tourist arrivals, but differently from the literature, we consider, for the first time, two additional variables reflecting the pulse of the market, namely the Infectious Disease Equity Market Volatility Tracker index and the country’s business confidence. Table 1 shows a selected group of recently published studies concerning the relationship between tourism demand and traditional and/or alternative factors.

### 3. Methodology and data

#### 3.1. Methods

The number of foreign and domestic arrivals<sup>5</sup> at different establishment destinations is modelled using a set of (linear) panel data models and the (non-linear) fixed effects Poisson and Negative Binomial models. The latter models are suited for count-dependent variables, such as our case, since arrivals, denoted by *Tour*, take non-negative integer values, i. e.  $Tour \in N_0 = \{0, 1, 2 \dots\}$ . In the fixed effect panel data model, the dependent variable is the natural logarithm of the variable *Tour*:

$$\log(Tour_{it}) = \alpha_0 + \delta_i + \beta' x_{it} + \gamma' z_t + \varepsilon_{it} \tag{1}$$

$i = 1, \dots, N;$   
 $t = 1, \dots, T$

The subscript *i* denotes the cross-section dimension, explicitly the selected group of  $N = 9$  EU countries (i.e. Croatia, Cyprus, France, Greece, Italy, Malta, Portugal, Slovenia and Spain), and *t* is the time dimension: January 2010–March 2022.  $\alpha_0$  is the constant term,  $x_{it}$  is the vector that includes traditional, psychological, and technological explanatory variables depending on both *i* and *t*, while  $z_t$  includes explanatory variables depending only on *t*.

$\beta$  and  $\gamma$  are the vectors of parameters to estimate,  $\varepsilon_{it}$  is the idiosyncratic error term assumed to be independently and identically distributed over time and across cross-sectional units.  $\delta_i$  represents the time-invariant individual country’s effect, i.e. each country’s unobserved time-invariant specific heterogeneity. The central assumption of the fixed-effects model is that the explanatory variables are correlated with  $\delta_i$  while continuing to assume that  $x_{it}$  is uncorrelated with  $\varepsilon_{it}$ . Conversely, a random-effects model assumes no correlation between  $\delta_i$  and the regressors.

Since it is impossible to estimate all the country dummies  $\delta_i$  and the intercept  $\alpha_0$ , due to the dummy variable trap, we consider the restriction  $\delta_{CROATIA} = 0$ , so that

$$E[\log(Tour_{it}) | x_{it} = x, z_t = z] = \alpha_0 + \beta' x + \gamma' z \tag{2}$$

<sup>5</sup> “An arrival is defined as a person who arrives at a tourist accommodation establishment and checks in. No age limit is applied: children are counted even if the overnight stays of children are free of charge. The arrivals of same-day visitors spending only a few hours during the day (no overnight stay) at the establishment are excluded from accommodation statistics” (Eurostat, 2013).

when the country is Croatia and

$$E[\log(Tour_{it}) | x_{it} = x, z_t = z] = \alpha_0 + \delta_i + \beta' x + \gamma' z \tag{3}$$

for all the remaining countries.

Being *Tour* a discrete variable, its distribution only places probability mass at nonnegative integer values. Poisson count models accommodate this property of the distribution. Thus, we assume that the tourist arrivals in country *i* during month *t* have a Poisson distribution with intensity  $\lambda_{it}$  where

$$\lambda_{it} = \exp(\alpha_0 + \delta_i + \beta' x_{it} + \gamma' z_t) \tag{4}$$

$i = 1, \dots, N$   
 $t = 1, \dots, T$

Therefore, the probability mass function is given by:

$$P(Tour_{it} = n) = \frac{e^{-\lambda_{it}} \lambda_{it}^n}{n!} \tag{5}$$

$n = 0, 1, 2 \dots$

The first moment and the variance are:

$$E(Tour_{it}) = \lambda_{it} \tag{6}$$

$$Var(Tour_{it}) = \lambda_{it} \tag{7}$$

Eqs. (6) and (7) show that mean and variance are equal, i.e. the so-called equidispersion property of the Poisson distribution. Negative binomial regressions are also appropriate for modelling count-dependent variables, especially when they are over-dispersed, i.e. when the count outcome variable has a variance larger than the mean. In the case of the Negative Binomial model, the probability mass function is

$$P(Tour_{it} = n) = \frac{\Gamma(\alpha^{-1} + n)}{n! \Gamma(\alpha^{-1})} q_{it}^{\alpha^{-1}} (1 - q_{it})^n \tag{8}$$

$n = 0, 1, 2 \dots$

In the formulation (8)  $\Gamma(\bullet)$  denotes the gamma function and  $q_{it} = \frac{\alpha^{-1}}{\alpha^{-1} + \lambda_{it}}$ , where  $\alpha > 0$  is another parameter to estimate. Mean and variance in this model are given by

$$E(Tour_{it}) = \lambda_{it} \tag{9}$$

$$Var(Tour_{it}) = \lambda_{it} + \alpha \lambda_{it}^2 \tag{10}$$

In light of (9)–(10), the Negative Binomial model captures overdispersion.

In both the Poisson and the Negative Binomial models, and similar to the linear model, we assume that the reference country is Croatia so that

$$E[Tour_{it} | x_{it} = x, z_t = z] = \exp(\alpha_0 + \beta' x + \gamma' z) \tag{11}$$

when country *i* is Croatia and

$$E[Tour_{it} | x_{it} = x, z_t = z] = \exp(\alpha_0 + \delta_i + \beta' x + \gamma' z) \tag{12}$$

for all the other countries. The model is estimated using the Maximum Likelihood method based on the probability function (5) or (8). We calculate Heteroskedasticity and Autocorrelation consistent covariance matrices for the estimated model parameters for both the linear and Poisson and Negative Binomial panel models.

#### 3.2. Data and variables

We have collected monthly data mainly from Eurostat and FRED St. Louis and seasonally adjusted the unadjusted series with the Census X-12-ARIMA methodology. The dependent variable *Tour<sub>it</sub>* is the number of arrivals at tourism establishments of country *i* in month *t*. We consider four types of arrivals:

**Table 1**  
Selected Literature's Sample on Tourism demand.

Study	Focus	Research period	Methodology	Dependent Variable	Determinants of tourism demand
Balcilar, Aghazadeh, and Ike (2021)	OECD Countries	1995–2016	Panel Cointegration	Tourism expenditure	GDP, Employment, Exchange rate
Balli et al. (2018)	8 OECD Countries	1997 M1–2017M8	Wavelet analysis	International tourist arrivals	Country-specific, Global epu
Esquivias et al. (2021)	Indonesia	1989–2020	Autoregressive Integrated Moving Average Model	International tourist arrivals	GDP, Prices, Dummy Terrorist Attack, Financial Crisis 2008.
Fotiadis et al. (2021)	World	1998–2020	Long-Short Term Memory Neural Network and a Generalized Additive Model	International tourist arrivals	COVID-19 outbreak, Trend, Lagged tourist arrivals
Ghosh (2022)	Australia	2007–2020	Dynamic Panel Analysis	International tourist arrivals	Income, CPI, Exchange Rate, Global Economic Uncertainty, Economic Policy Uncertainty, Pandemic
Hailemariam and Ivanovski (2022)	US	1999–2020	Structural Vector Autoregression model	US tourism net export expenditures	World Industrial Production, Exchange Rate, Economic Policy Uncertainty
Işık et al. (2020)	US	1996–2017	Dynamic Ordinary Least Squares	International tourist arrivals from Mexico and Canada to US	Industrial Production, Exchange Rate, Economic Policy Uncertainty
Karabulut et al. (2020)	129 Countries	1996–2018	Panel Fixed Effects Models; Difference Generalized Method of Moments	International tourist arrivals	Pandemics Index, GDP, Trade Openness, Exchange Rate
Kocak et al. (2022)	US	1999–2020	Non-quantile and Quantile Panel models	International tourist arrivals	GDP, Exchange Rate, Jet Fuel, World Pandemic Uncertainty Index, Discussion about Pandemics Index
Kuok et al. (2022)	31 Countries	2000Q1 to 2019Q4	Global Vector Autoregressive model	Real travel	Income, Exchange Rate, EPU, oil
Lee et al. (2021)	16 Countries	2005–2017	Panel Analysis with Common Correlated Effects Mean Group and Augmented Mean Group	Tourism receipts and arrivals	GDP, Exchange Rate, Price level, Tourism-related facilities, Geopolitical risk, Pandemic outbreaks dummy (e.g. Ebola)
Navarro-Chávez et al. (2022)	Mexico	2010–2018	Dynamic Ordinary Least Squares; Fully Modified Least Squares	International tourist arrivals	Income, Exchange Rate, EPU
Plzáková and Smeral (2022)	Euro Area	1995–2020	Ordinary Least Squares	Tourist expenditures for outbound travel	GDP, Prices of Tourism Imports, Dummy COVID-19
Santana-Gallego et al. (2020)	171 Countries	1995–2013	Panel Fixed Effects Models	International tourist arrivals	GDP, Exchange Rate, Voice and Accountability, Crime Rate, Corruption, Terrorism

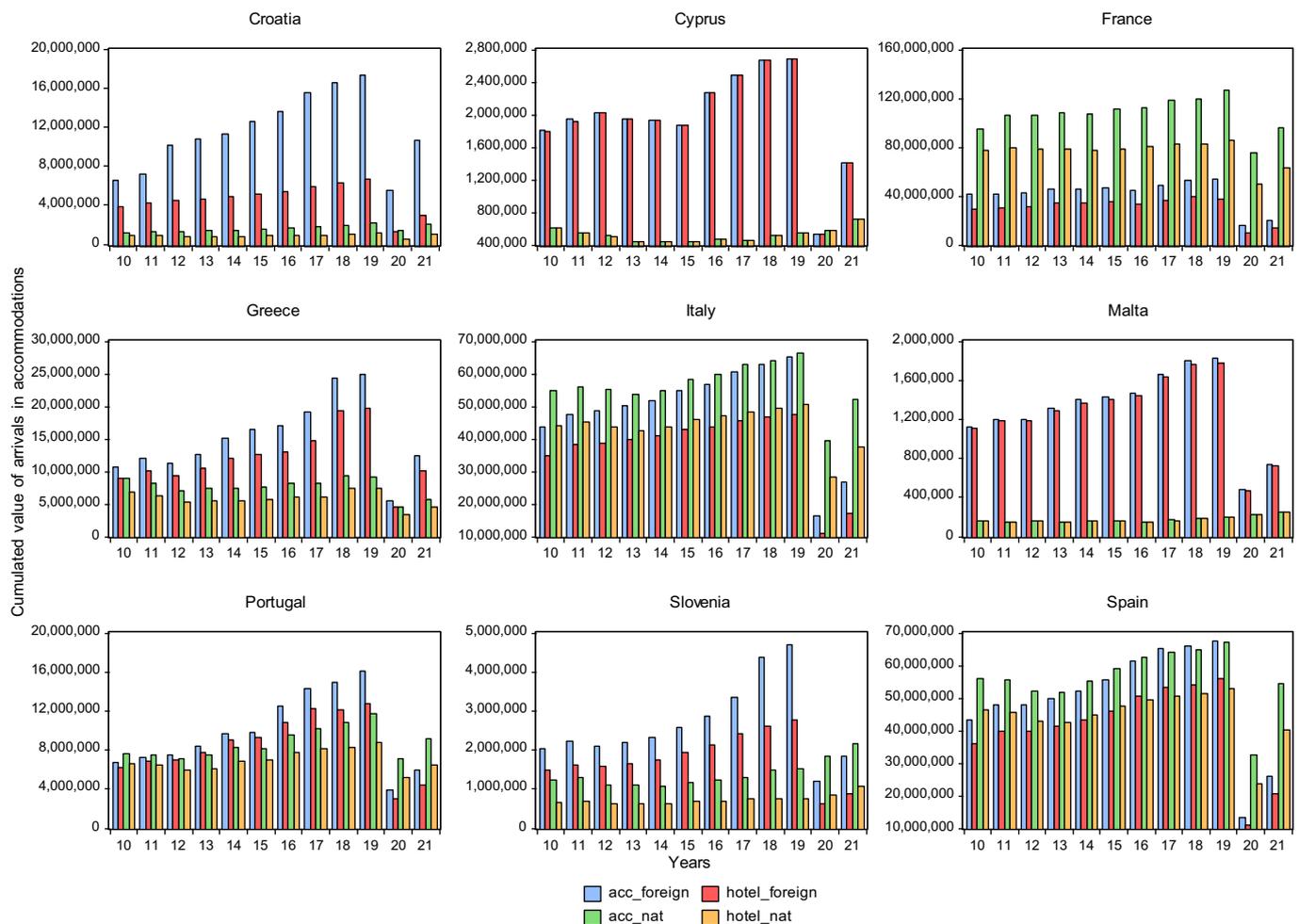
Source: Authors' Elaborations.

**Table 2**  
List of Variables and Sources.

Variable	Full Name	Source of data
acc_foreign	Foreign tourist arrivals at holiday and other short-stay accommodation	Eurostat tour_occ_arm <a href="https://ec.europa.eu/eurostat/web/main/data/database">https://ec.europa.eu/eurostat/web/main/data/database</a>
hotel_foreign	Foreign tourist arrivals at hotels	Eurostat tour_occ_arm <a href="https://ec.europa.eu/eurostat/web/main/data/database">https://ec.europa.eu/eurostat/web/main/data/database</a>
acc_nat	National (domestic) tourist arrivals at holiday and other short-stay accommodation	Eurostat tour_occ_arm <a href="https://ec.europa.eu/eurostat/web/main/data/database">https://ec.europa.eu/eurostat/web/main/data/database</a>
hotel_nat	National (domestic) tourist arrivals at hotels	Eurostat tour_occ_arm <a href="https://ec.europa.eu/eurostat/web/main/data/database">https://ec.europa.eu/eurostat/web/main/data/database</a>
rex	Real broad effective exchange rate	FRED St. Louis <a href="https://fred.stlouisfed.org">https://fred.stlouisfed.org</a>
u	Harmonized unemployment rate	Eurostat ei_lmhr_m <a href="https://ec.europa.eu/eurostat/web/main/data/database">https://ec.europa.eu/eurostat/web/main/data/database</a>
cip	Country's industrial production proxy for domestic income	Eurostat STS_INPR_M <a href="https://ec.europa.eu/eurostat/web/main/data/database">https://ec.europa.eu/eurostat/web/main/data/database</a>
business_sent	Business sentiment	Eurostat ei_bssi_m_r2 <a href="https://ec.europa.eu/eurostat/web/main/data/database">https://ec.europa.eu/eurostat/web/main/data/database</a>
museum	Virtual museum	Google trend
wip	World industrial production proxy for world income	FRED St. Louis <a href="https://fred.stlouisfed.org">https://fred.stlouisfed.org</a>
oil	Crude oil, Brent	FRED St. Louis <a href="https://fred.stlouisfed.org">https://fred.stlouisfed.org</a>
disease_track	Infectious disease equity market volatility tracker	FRED St. Louis <a href="https://fred.stlouisfed.org">https://fred.stlouisfed.org</a>
epu	Economic policy uncertainty	<a href="https://www.policyuncertainty.com/">https://www.policyuncertainty.com/</a>
covid	Coronavirus	Dummy variable, authors' computation

- 1) foreign tourist arrivals at holiday and other short-stay accommodation; camping grounds, recreational vehicle parks and trailer parks;
- 2) foreign tourist arrivals at tourist hotels and similar accommodations;
- 3) domestic tourist arrivals at holiday and other short-stay accommodations; camping grounds, recreational vehicle parks and trailer parks;
- 4) domestic tourist arrivals at tourist hotels and similar accommodations.

Our explanatory variables  $x_{it}$  and  $z_t$  in eq. 1 belong to four channels that could influence tourist arrivals, namely i) a traditional macroeconomic channel, ii) an uncertainty-sentiment channel, iii) a technological channel and iv) a channel related to health developments. Notably, the traditional macroeconomic channel includes the classical variables reflecting prices and income (proxied by industrial production) used in the tourism demand literature (e.g. Rosselló Nadal & Santana-Gallego, 2022).



**Fig. 1.** Tourist Arrivals at different accommodation establishments. The histograms report the years on the x-axis and the cumulated value of arrivals in the accommodations on the y-axis. Legend: *acc\_foreign* = foreign tourist arrivals at holiday and other short-stay accommodation; *hotel\_foreign* = foreign tourist arrivals at hotels; *acc\_nat* = national (domestic) tourist arrivals at holiday and other short-stay accommodation; *hotel\_nat* = national (domestic) tourist arrivals at hotels.

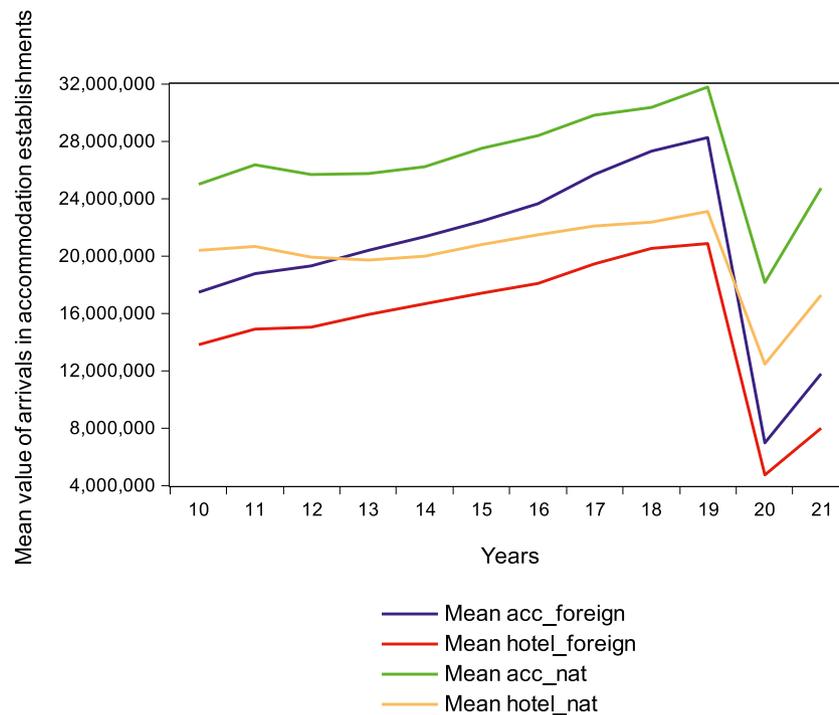


Fig. 2. Total Tourists at accommodation establishments. Mean Values. The graph reports the year  $t$  on the x-axis and the mean value of arrivals in accommodation establishments during year  $t$ ,  $\frac{1}{N} \sum_{i=1}^N Tour_{it}$ , in the y-axis. Legend: see Fig. 1.

Price variables comprise:

- The real broad effective exchange rate ( $rex_{it}$ ) for each country in month  $t$ . The variable, reflecting the cost of living in a country, mirrors the degree of a country’s international competitiveness, i.e. its ability to attract tourists (e.g. Algieri, 2014; Dogru, Sirakaya-Turk, & Crouch, 2017). A real appreciation increases the cost of living and reduces international competitiveness, while a real depreciation raises destination attractiveness since domestic prices become relatively cheaper than alternative destinations’ prices. The real effective exchange rate allows one to compare countries with the same currency but with different domestic price dynamics. Since the countries under investigation have the same currency (except for Croatia), competitiveness is due to country price differences (Algieri & Bracke, 2011; Kumar, Misra, & Chan, 2022).
- The crude oil price ( $oil_t$ ). We consider the monthly price of BRENT as a proxy for the price of travel (e.g. Algieri & Kanellopoulou, 2009; Kuok et al., 2022). The oil price is an essential factor driving tourism, as it influences the cost of transport and the production of tourism services. Therefore, higher prices are expected to raise transport costs and thus reduce tourist arrivals. However, if cultural or leisure benefits that draw tourists outweigh transport costs, the coefficient sign on arrivals can be positive (Adeola et al., 2017; Demir, Simonyan, Chen, & Lau, 2020).

Income variables include:

- The world industrial production ( $wip_t$ ), a proxy for global GDP or income at a monthly frequency that drives the international tourism demand. Since income (or GDP) is only available at a quarterly frequency but is highly correlated with industrial production, the tourism literature has amply considered the latter as a covariate (e.g. Hailemariam & Ivanovski, 2022; İşık et al., 2020). Hence, we expect that an increase in  $wip$  raises consumption and, thus, international tourism demand.

- Country  $i$  industrial production ( $cip_{it}$ ), a proxy for domestic income or GDP at a monthly frequency that drives the domestic tourism demand. However, since a possible caveat of the study is that industrial production could underestimate GDP (Stanger, 2020), we have included in our analysis also a business sentiment variable (see the uncertainty-sentiment channel below) that allows us to capture more comprehensively the ‘pulse’ of the country’s economic activity. We expect that an increase in domestic income increases national arrivals.
- The harmonized unemployment rates in percentage ( $u_{it}$ ). This variable reflects the state of an economy. A lower unemployment rate suggests an increase in tourism demand due to available income. The variable enters only the specifications referred to domestic arrivals. The unemployment rate has been considered by Gounopoulos, Petmezias, and Santamaria (2012) and Balcilar et al. (2021) to examine the demand for tourism in Greece and in OECD countries, respectively.

The uncertainty-sentiment channel comprises:

- The business sentiment ( $business\_sent_{it}$ ). The variable summarises the expectations of economic operators of country  $i$  in month  $t$ . It reveals the mood of the country’s operators and therefore signals the economic conditions in country  $i$ .
- The Infectious Disease Equity Market Volatility Tracker ( $disease\_track_t$ ). It is a forward-looking uncertainty measure constructed considering the newspaper-based economic uncertainty, the uncertainty drawn from business expectations surveys and the stock market volatility. This index seizes the ‘vibes’ in the economy and quantifies the increase in health-related uncertainty over time. Although the variable has been constructed for the US, it can be used in the European context since Western economies (in particular, the US and EU) are highly interconnected. It should be mentioned that the estimations could be more precise if a specific index were available at a country level.

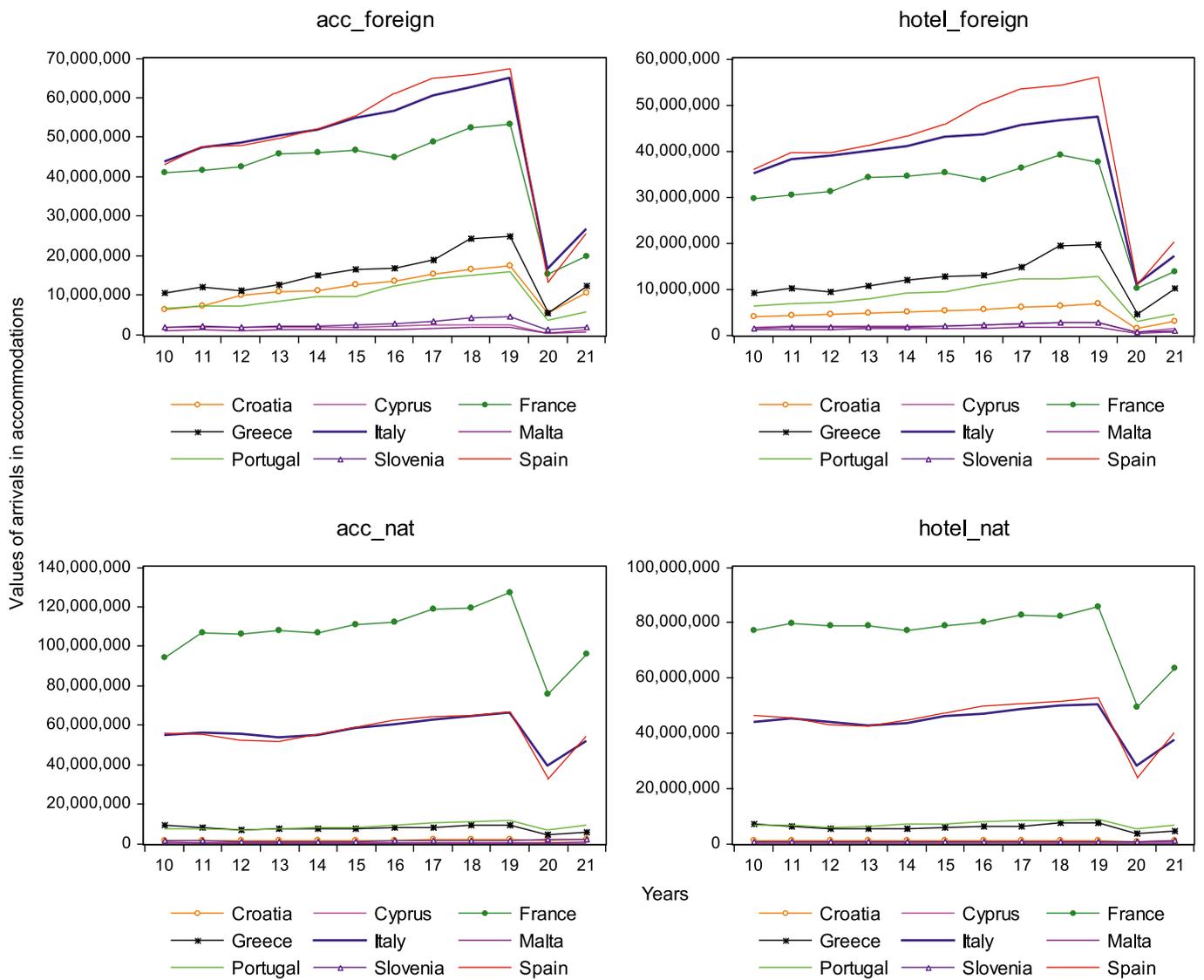


Fig. 3. Tourists at accommodation establishments. The graphs report the years on the x-axis and the values of arrivals in different types of accommodations on the y-axis. Legend: see Fig. 1.

Table 3  
Descriptive statistics.

Variables	Mean	Dev. Standard	Min	Max	Skewness	Kurtosis	Obs
acc_foreign	1,669,928	2,129,487	758	9,254,845	1.499	4.372	1323
hotel_foreign	1,271,607	1,588,189	70	6,595,367	1.421	4.026	1323
acc_nat	2,205,899	3,317,540	1483	1.70E+07	1.820	6.110	1323
hotel_nat	1,658,562	2,326,395	270	8,961,093	1.304	3.409	1323
exchange rate	96.052	3.430	85.570	103.570	-0.653	2.881	1323
u	11.795	5.851	3.100	28.100	0.895	3.135	1323
cip	104.717	9.485	58.200	139.000	1.019	5.373	1323
business sent	98.951	10.142	53.800	118.900	-0.671	3.374	1323
museum	3.407	6.281	5.000	100.000	6.698	8.120	1323
wip	98.889	3.789	84.960	104.180	-1.084	4.104	1323
crude oil	76.174	26.323	18.380	125.450	0.158	1.828	1323
disease track	3.603	7.860	0.090	50.220	2.988	13.386	1323
epu	207.792	58.531	111.800	433.280	1.264	5.449	1323

Note: *acc\_foreign* = foreign tourist arrivals at holiday and other short-stay accommodation; *hotel\_foreign* = foreign tourist arrivals at hotels; *acc\_nat* = national (domestic) tourist arrivals at holiday and other short-stay accommodation; *hotel\_nat* = national (domestic) tourist arrivals at hotels.

- The economic policy uncertainty (*epu*). It is a variable that quantifies newspaper coverage of policy-related economic uncertainty, included in a few studies on tourism demand (Dragouni et al., 2016;

Ghosh, 2022; Işık et al., 2020). Due to the unavailability of data for some Mediterranean countries, we have considered the *epu* Index for Europe.

**Table 4**  
Panel unit root test.  $H_0$ : Panels contain unit roots vs  $H_1$ : Panels are stationary. ADF regressions, LLC and B: 1 lag.

	Levin-Lin-Chu (LLC)/standard ADF unit-root test		Breitung (B) unit-root test	
	Adjusted-t	p-value	Lambda stat	p-value
acc_foreign	-17.901	<0.001	-6.099	<0.001
acc_nat	-15.777	<0.001	-8.441	<0.001
hotel_foreign	-16.121	<0.001	-4.806	<0.001
hotel_nat	-14.047	<0.001	-7.026	<0.001
museum	-18.042	<0.001	-16.187	<0.001
business sent	-3.086	0.001	-4.885	<0.001
epu <sup>a</sup>	-6.201	<0.001	-	-
wip <sup>a</sup>	-2.582	0.011	-	-
disease track <sup>a</sup>	-2.573	0.010	-	-
exchange rate	-2.473	0.007	-1.666	0.048
crude oil <sup>a</sup>	-2.247	0.044	-	-
unemployment rate	2.093	0.982	3.859	0.999
cip	-7.648	<0.001	-2.792	0.003

<sup>a</sup> Standard ADF unit root, for the series epu, world industrial production, crude oil and disease track.  $H_0$ : The series has a unit root vs  $H_1$ : The series is stationary.

The technological channel contains:

- Museum ( $museum_{it}$ ), a variable that expresses the average interest of virtual museums for country  $i$  in month  $t$  according to Google Trends, i.e. Google search volumes for keywords related to museum experiences online. Extending Yang, Pan, and Song (2014) and Bakirtas and Gulpinar Demirci (2022) reasoning, the variable would imply a potential activity of taking an online visit across memory institutions. Google Trends provide the Search Volume Index, i.e. the quantity of searched term or combination of words scaled and normalised over time. This index reveals the popularity and interest of a search query at a given time for global or specific geographical areas. It varies between 0 and 100, where 100 is the maximum search interest for the time and location selected. For our analysis, the keywords in Google Trends were ‘virtual museum tour’ and ‘virtual field trips’, ranked first and second top-trending Google searches by ‘Year in Search’. The query ‘virtual museum’ was also done in the national language. Internet searches have signalling properties since spontaneous actions and behaviours of people trigger them (Da, Engelberg, & Gao, 2015). Furthermore, Google Trends have several advantages, including the high volume and frequency of data and the quick sensitivity to changes in user behaviour. In this case, it is possible to identify tourist needs, interests and intentions (Li, Pan, Law, & Huang, 2017). The sign of the variable museum can be positive or negative depending on the prevalence of the substitution effect (physical or virtual presence) or complementary effect (the virtual experience is accompanied by physical presence in the short-term).

The health channel includes:

- The dummy covid ( $covid_t$ ), a binary variable that takes a value of 0 before the pandemic, i.e. from January 2010 until December 2019, and a value of 1 afterwards.

In synthesis, vector  $x_{it}$  is made by:

$$x_{it} = (rex_{it}, u_{it}, cip_{it}, business\_sent_{it}, museum_{it}) \tag{13}$$

Vector  $z_t$  includes:

$$z_t = (wip_t; oil_t; disease\_track_t; epu_t; covid_t) \tag{14}$$

Table 2 displays the list of variables and data sources.

### 3.3. Variable dynamics

The yearly dynamics of the dependent variable distinguished by the type of tourist arrivals can be gleaned from Fig. 1. Foreign tourists drive the tourism sector in Croatia, Cyprus, Greece, Malta and Slovenia. Conversely, France has a tourism sector driven by domestic arrivals. Italy and Spain are characterised by an almost balanced mix of domestic and foreign tourists. In the first two years of the sample, Portugal registered a larger number of domestic tourists, while afterwards, this pattern reverted to change again in the latest years. Although before the pandemics, foreign and domestic tourist arrivals experienced uninterrupted growth (Fig. 2), COVID-19 exerted a domino effect for all the countries with significant drops in arrivals (Fig. 3). The contraction in percentage terms (year-on-year change) in 2020 has been more marked for Spain (-80%), Greece (-79%), Portugal (-76%) and Italy (-75%) (Elaborations on Eurostat, 2022).

Table 3 shows the descriptive statistics. On average, holidays, short-stay accommodations and hotels record a more pronounced number of national tourist arrivals than foreign arrivals. The explanatory variables display a low correlation except for the pair *disease\_track* and *COVID-19*; thus, the two variables do not enter the same econometric specifications. The response variables (tourist arrivals) are strongly skewed to the right implying that OLS regressions could be inappropriate. Indeed, count data often follow skewed and non-linear distributions, so some type of Poisson or Negative Binomial analysis might be more suitable for the analysis.

## 4. Empirical analysis

### 4.1. Unit root tests and panel results

Tourist arrival equations were estimated using different panel data models. We initially checked for the stationarity of the series to ascertain whether to adopt a panel cointegration analysis. To this purpose, we have applied the Levin-Lin-Chu (LLC) unit root test to the vector  $x_{it}$  that contains variables changing in time and across countries, and the classical Augmented Dickey-Fuller (ADF) test to the vector  $z_t$  that includes variables varying in time but not across countries (namely, crude oil, world GDP, *epu* and the infectious disease tracker). The LLC test is very suited when the number of periods (147 months in our case) is larger than the number of countries (9 in our case).<sup>6</sup> The test involves fitting an Augmented Dickey-Fuller regression for each country with a number of lags selected on the basis of the Akaike Information Criterion (AIC). The LLC and the ADF results (Table 4) indicate that all variables, except for the unemployment rate,<sup>7</sup> are stationary since the null hypothesis of ‘panel/classical unit root’ is rejected at a 5% significance level. This finding suggests that the variables considered in the analysis follow a stationary process and there is no need for a panel cointegration analysis. To corroborate the results, we have also performed the Breitung panel unit root test (B) which confirms the previous findings for the vector  $x_{it}$ .

We have therefore fitted linear fixed/random effects panel models to log-transformed arrivals seasonally adjusted. The literature has extensively discussed the identification of the two types of models (Baltagi, 2013): random-effects are more appropriate when  $N$  “individuals-countries” are randomly drawn from a large population; fixed-effects are preferable when attention is on  $N$ -specific individuals. Since the countries under investigation are those representatives of the Mediterranean EU group, the choice of the countries is not random. Formally, the Hausman test (bottom line of Table 5) recommended the adoption of

<sup>6</sup> See Maddala and Wu (1999).

<sup>7</sup> To avoid spurious regression, the unemployment rate has been considered in log first differences (i.e. the rate of change of the unemployment rate or the growth rate of the unemployment rate) to have a stationary series.

**Table 5**  
Fixed-Effect LSDV Panel estimations.

Panel A. Holiday and Short-stay accommodations						
	(1)	(2)	(3)	(4)	(5)	(6)
	l_acc_foreign	l_acc_foreign	l_acc_foreign	l_acc_nat	l_acc_nat	l_acc_nat
covid	-0.885 *** (0.131)		-1.097 *** (0.066)	-0.168 *** (0.060)		-0.144 ** (0.060)
museum	-0.024 *** (0.005)	-0.021 *** (0.005)	-0.023 *** (0.005)	-0.0224 *** (0.003)	-0.021 *** (0.003)	-0.0224 *** (0.003)
business sent	3.143 *** (0.310)	2.525 *** (0.310)	2.921 *** (0.299)	0.529 ** (0.225)	0.855 *** (0.208)	0.736 *** (0.213)
epu	0.232 ** (0.106)			-0.200 *** (0.066)		
wip	5.649 *** (1.212)	7.933 *** (0.902)	3.854 *** (0.795)			
trend	-0.0035 * (0.002)	-0.003 *** (0.001)		-0.0032 *** (0.001)	-0.003 *** (0.001)	-0.0038 *** (0.001)
disease track		-0.245 *** (0.027)			-0.049 *** (0.015)	
exchange rate		-2.377 ** (1.120)			-2.375 *** (0.684)	
crude oil	0.410 *** (0.094)		0.503 *** (0.071)	0.180 *** (0.050)		0.214 *** (0.050)
u (rate of change)				-1.816 *** (0.542)		-1.903 *** (0.543)
cip				4.922 *** (0.572)	5.158 *** (0.544)	4.669 *** (0.565)
constant	-31.50 *** (5.152)	-45.42 *** (6.834)	-19.75 *** (3.085)	-12.43 *** (2.141)	-25.34 *** (3.666)	-12.55 *** (2.166)
N Obs	1318	1318	1318	1320	1320	1320
R2	0.380	0.393	0.377	0.299	0.287	0.293
AIC	3373.1	3343.3	3376.5	1988.5	2015.5	1997.3
BIC	3414.5	3379.6	3407.6	2035.1	2051.8	2038.8
F	114.1	140.6	157.6	69.09	87.56	76.84
Hausman_p-value	0.000	0.000	0.001	0.000	0.001	0.000

Panel B Hotels and similar accommodations						
	(7)	(8)	(9)	(10)	(11)	(12)
	l_hotel_foreign	l_hotel_foreign	l_hotel_foreign	l_hotel_nat	l_hotel_nat	l_hotel_nat
covid	-0.835 *** (0.117)		-1.203 *** (0.059)	-0.148 *** (0.054)		-0.126 ** (0.054)
museum	-0.020 *** (0.005)	-0.018 *** (0.005)	-0.019 *** (0.005)	-0.0190 *** (0.003)	-0.018 *** (0.003)	-0.0190 *** (0.003)
business sent	3.303 *** (0.277)	2.625 *** (0.278)	2.973 *** (0.269)	0.593 *** (0.202)	0.904 *** (0.188)	0.785 *** (0.191)
epu	0.312 *** (0.095)			-0.185 *** (0.059)		
wip	6.967 *** (1.084)	8.951 *** (0.808)	3.884 *** (0.714)			
trend	-0.006*** (0.002)	-0.006 *** (0.001)		-0.0045 *** (0.001)	-0.005 *** (0.001)	-0.005 *** (0.001)
disease track		-0.237 *** (0.024)			-0.035 ** (0.014)	
exchange rate		-1.523 (1.003)			-1.896 *** (0.617)	
crude oil	0.394 *** (0.084)		0.569 *** (0.064)	0.190 *** (0.045)		0.224 *** (0.045)
u (rate of change)				-1.966 *** (0.486)		-2.044 *** (0.487)
cip				5.368 *** (0.513)	5.805 *** (0.491)	5.125 *** (0.507)
constant	-38.62 *** (4.608)	-46.69 *** (6.121)	-20.61 *** (2.772)	-15.11 *** (1.919)	-26.49 *** (3.309)	-15.10 *** (1.943)
N Obs	1318	1318	1318	1320	1320	1320
R2	0.461	0.471	0.453	0.364	0.344	0.358
AIC	3078.9	3052.8	3094.5	1702.7	1744.7	1712.0
BIC	3120.4	3089.1	3125.6	1749.3	1781.0	1753.4
F	159.3	193.5	216.3	92.49	113.8	103.3
Hausman_p-value	0.002	0.000	0.000	0.002	0.000	0.000

All variables are in logs except for dummy variables. Hausman test: The null hypothesis is that the preferred model is random effects versus the alternative fixed effects. Discroll-Kraay Standard errors are in parentheses. Asterisks \*\*\*, \*\* and \* denote significance at the 1, 5 and 10% level, i.e. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

**Table 6**  
Poisson estimations.

Panel A Holiday and Short-stay accommodations						
	(1)	(2)	(3)	(4)	(5)	(6)
	acc_foreign	acc_foreign	acc_foreign	acc_nat	acc_nat	acc_nat
covid	-0.786 *** (0.073)		-0.788 *** (0.070)	-0.209 *** (0.022)		-0.218 *** (0.019)
museum	-0.0417 *** (0.009)	-0.0368 *** (0.008)	-0.0419 *** (0.009)	-0.0398 *** (0.005)	-0.0399 *** (0.003)	-0.0384 *** (0.004)
business sent	1.230 *** (0.299)	0.618 ** (0.264)	1.249 *** (0.294)	0.390 ** (0.155)		0.484 *** (0.128)
epu	-0.00148 (0.085)			-0.170 *** (0.047)		
wip	1.567 ** (0.635)	2.554 *** (0.663)	1.502 ** (0.640)			
disease track		-0.213 *** (0.018)			-0.0437 *** (0.007)	
exchange rate		-1.055 (0.928)				
crude oil	0.177 *** (0.067)		0.195 *** (0.069)		0.0838 *** (0.026)	0.117 *** (0.027)
u (rate of change)				-1.306 *** (0.094)	-1.137 (0.886)	-1.240 *** (0.090)
cip					1.079 *** (0.235)	
constant	-0.549 (2.853)	3.866 (6.041)	0.383 (2.690)	11.11 *** (1.782)	6,809 ** (2.874)	9,747 *** (1.406)
<i>N Obs</i>	1323	1323	1323	1323	1323	1323
<i>pseudo R<sup>2</sup></i>	0.761	0.764	0.761	0.932	0.932	0.931
<i>AIC</i>	748,168,346.5	736,970,798.9	747,512,712.8	369,327,157.3	370,849,272.2	373,520,615
<i>BIC</i>	748,168,424.3	736,970,871.5	747,512,785.4	369,327,188.3	370,849,298.1	373,520,641
chi2 p-value	0.000	0.000	0.000	0.000	0.000	0.000

Panel B Hotels and similar accommodations						
	(7)	(8)	(9)	(10)	(11)	(12)
	hotel_foreign	hotel_foreign	hotel_foreign	hotel_nat	hotel_nat	hotel_nat
covid	-0.900 *** (0.064)		-0.895 *** (0.062)	-0.285 *** (0.019)		-0.233 *** (0.049)
museum	-0.0323 *** (0.008)	-0.0281 *** (0.007)	-0.0331 *** (0.008)	-0.0281 *** (0.005)	-0.0289 *** (0.004)	-0.0263 *** (0.005)
business sent	1.254 *** (0.253)	0.540 ** (0.220)	1.250 *** (0.248)	0.593 *** (0.163)		0.543 *** (0.206)
epu	0.0532 (0.070)			-0.133 *** (0.039)		
wip	1.571 *** (0.560)	2.663 *** (0.588)	1.503 *** (0.565)			
disease track		-0.233 *** (0.015)			-0.0560 *** (0.006)	
exchange rate		-1.137 * (0.708)				
crude oil	0.213 *** (0.057)		0.220 *** (0.058)		0.0998 *** (0.013)	0.139 *** (0.040)
u (rate of change)				-1.226 *** (0.068)	-1.0352 (0.572)	
cip					1.427 *** (0.212)	1.120 *** (0.334)
constant	-2.178 (2.563)	3.190 (5.299)	-0.626 (2.417)	8.853 *** (1.327)	4.327 * (2.348)	3.052 ** (1.369)
<i>N Obs</i>	1323	1323	1323	1323	1323	1323
<i>pseudo R<sup>2</sup></i>	0.825	0.826	0.825	0.940	0.940	0.941
<i>AIC</i>	403,616,931.0	400,413,686.0	403,214,033.9	152,209,730.6	153,578,584.5	153,548,749.1
<i>BIC</i>	403,617,008.9	400,413,758.6	403,214,106.5	152,209,761.6	153,578,610.4	153,548,821.7
chi2 p-value	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses. Asterisks \*\*\*, \*\* and \* denote significance at the 1, 5 and 10% level, i.e. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

fixed-effects because the null hypothesis, that the random-effects provide consistent estimates, is rejected.

We have further tested for cross-dependence and corrected the standard errors by following the Driscoll-Kraay approach. To account for country differences, we have considered the Least Square Dummy Variable (LSDV) model - within the fixed-effects models - that generates the same coefficient estimates of the fixed-effects but allows us to

distinguish each specific intercept since each dummy absorbs the effects particular to each country.

Table 5 reports the results of different specifications for the fixed-effects models. We can interpret the estimated coefficients of the explanatory variables, which are in logs, as elasticities and thus independent from the measurement unit of the variables. Table A.1 in the appendix presents the estimated country effects.

**Table 7**  
Negative Binomial estimations.

Panel A Holiday and Short-stay accommodations						
	(1)	(2)	(3)	(4)	(5)	(6)
	acc_foreign	acc_foreign	acc_foreign	acc_nat	acc_nat	acc_nat
covid	-0.768 *** (0.074)		-0.767 *** (0.073)	-0.0529 (0.054)		-0.0563 (0.054)
museum	-0.0191 *** (0.006)	-0.0171 *** (0.006)	-0.0188 *** (0.006)	-0.0255 *** (0.005)	-0.0251 *** (0.005)	-0.0258 *** (0.005)
business sent	2.153 *** (0.334)	1.680 *** (0.291)	2.114 *** (0.324)	0.841 *** (0.263)		0.887 *** (0.251)
epu	0.0787 (0.083)			-0.153 *** (0.054)		
wip	3.763 *** (0.622)	5.283 *** (0.724)	3.715 *** (0.616)			
disease track		-0.216 *** (0.019)			-0.0286 ** (0.013)	
exchange rate		-1.353* (0.756)				
crude oil	0.301 *** (0.085)		0.289 *** (0.082)		0.0899 ** (0.041)	0.169 *** (0.058)
u (rate of change)				-1.328 *** (0.065)	-1.190 ** (0.592)	-1.294 *** (0.061)
cip					1.302 *** (0.339)	
constant	-16.42 *** (3.359)	-24.55 *** (7.726)	-14.18 *** (3.031)	8.456 *** (1.874)	5.867 *** (1.766)	7.753 *** (1.436)
lnalpha	-0.431 *** (0.056)	-0.443 *** (0.057)	-0.431 *** (0.056)	-1.320 *** (0.106)	-1.318 *** (0.106)	-1.315 *** (0.105)
N Obs	1323	1323	1323	1323	1314	1323
pseudo R <sup>2</sup>	0.044	0.045	0.044	0.095	0.095	0.095
AIC	38,399.9	38,379.5	38,398.8	35,997.6	35,998.4	36,002.4
BIC	38,482.9	38,457.3	38,476.6	36,080.5	36,076.1	36,080.1
chi2 p-value	0.101	0.111	0.099	0.110	0.121	0.109

Panel B Hotels and similar accommodations						
	(7)	(8)	(9)	(10)	(11)	(12)
	hotel_foreign	hotel_foreign	hotel_foreign	hotel_nat	hotel_nat	hotel_nat
covid	-0.918 *** (0.062)		-0.913 *** (0.061)	-0.092* (0.049)		-0.085 ** (0.041)
museum	-0.0158 *** (0.006)	-0.0135 ** (0.006)	-0.015 ** (0.006)	-0.022 *** (0.005)	-0.022 *** (0.005)	-0.019 *** (0.005)
business sent	2.286 *** (0.296)	1.626 *** (0.253)	2.232 *** (0.287)	0.933 *** (0.252)		0.830 *** (0.210)
epu	0.123 * (0.069)			-0.0812 * (0.042)		
wip	3.475 *** (0.568)	5.294 *** (0.671)	3.427 *** (0.564)			
disease track		-0.257 *** (0.016)			-0.038*** (0.012)	
exchange rate		-1.235 * (0.770)				
crude oil	0.392 *** (0.074)		0.376 *** (0.071)		0.125 *** (0.036)	0.197 *** (0.050)
u (rate of change)				-1.251 *** (0.054)	-1.120 * (0.658)	
cip					1.432 *** (0.323)	1.316 *** (0.218)
constant	-17.66 *** (3.040)	-24.75 *** (7.134)	-14.68 *** (2.762)	6.353 *** (1.753)	4.399 *** (1.681)	0.534 (1.408)
lnalpha	-0.645 *** (0.064)	-0.653 *** (0.065)	-0.644 *** (0.064)	-1.528 *** (0.124)	-1.528 *** (0.127)	-1.548 *** (0.123)
N Obs	1323	1323	1323	1323	1314	1323
pseudo R2	0.051	0.051	0.051	0.104	0.104	0.104
AIC	37,516.1	37,502.1	37,515.8	35,290.1	35,052.0	35,260.4
BIC	37,599.1	37,579.9	37,593.6	35,373.1	35,129.7	35,338.2
chi2 p-value	0.102	0.115	0.101	0.112	0.122	0.104

Standard errors in parentheses. Asterisks \*\*\*, \*\* and \* denote significance at the 1, 5, 10% level, i.e. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ , lnalpha is the over-dispersion coefficient.

**Table 8**  
Marginal Effects (Negative Binomial Models).

Museum	Accom Foreign		Accom Domestic		Hotel Foreign		Hotel Domestic	
Country	dy/dx	t-stat	dy/dx	t-stat	dy/dx	t-stat	dy/dx	t-stat
Croatia	-32,386	-4.810	-4768	-6.891	-10,615	-4.320	-1997	-6.140
Cyprus	-5780	-5.170	-1468	-6.812	-4621	-4.381	-1069	-5.950
France	-133,570	-4.771	-323,329	-6.391	-76,945	-4.140	-164,442	-5.850
Greece	-45,002	-5.082	-25,424	-6.772	-28,866	-4.361	-13,723	-6.130
Italy	-193,226	-3.971	-216,892	-5.321	-111,125	-3.550	-112,162	-5.010
Malta	-3664	-5.173	-416	-6.101	-2871	-4.381	-310	-5.730
Portugal	-32,338	-4.572	-28,627	-6.150	-21,802	-3.971	-15,841	-5.590
Slovenia	-7573	-5.223	-3527	-6.571	-4109	-4.472	-1392	-5.990
Spain	-197,708	-3.991	-252,132	-5.311	-122,257	-3.552	-128,433	-5.021

covid	Accom Foreign		Accom Domestic		Hotel Foreign		Hotel Domestic	
country	dy/dx	t-stat	dy/dx	t-stat	dy/dx	t-stat	dy/dx	t-stat
Croatia	-487,377	-8.440	-25,214	-3.311	-223,661	-11.960	-19,701	-6.131
Cyprus	-86,982	-11.291	-7762	-3.330	-97,366	-13.351	-10,544	-5.950
France	-2,010,058	-12.500	-1,709,815	-3.511	-1,621,269	-17.032	-1,622,498	-6.601
Greece	-677,221	-8.920	-134,445	-3.030	-608,223	-10.520	-135,405	-5.510
Italy	-2,907,812	-12.490	-1,146,959	-3.551	-2,341,479	-15.120	-1,106,663	-6.740
Malta	-55,136	-12.971	-2199	-3.640	-60,495	-16.271	-3055	-6.580
Portugal	-486,642	-13.671	-151,386	-3.441	-459,391	-17.311	-156,295	-6.410
Slovenia	-113,964	-11.051	-18,649	-3.482	-86,589	-15.360	-13,736	-6.311
Spain	-2,975,265	-13.040	-1,333,312	-3.233	-2,576,025	-15.530	-1,267,201	-5.951

Note: dy/dx for the dummy is the discrete change from the base level (no covid).

Tables 6 and 7 show the findings for the panel Poisson models and the Negative Binomial models, respectively (with the country effects in Tables A.2 and A.3). The goodness-of-fit chi-squared test, with p-values equal to zero, indicates that Poisson models do not fit well (bottom of Table 6) due to the presence of over-dispersion in the data. We have, therefore, estimated Negative Binomial regression models appropriate to account for this characteristic (Table 7). The information criteria AIC and BIC also suggest that Negative Binomial models fit data better than Poisson models.

4.2. Discussion of the results

The results of the LSDV, Poisson and Negative Binomial panel models strongly suggest that all identified channels significantly impact arrivals. The coefficients associated with the world (country *i*) industrial production, a proxy for foreign (domestic) income, have the expected sign and are statistically significant. An increase in global (domestic) production raises international (national) demand for tourism. The latter is confirmed to be a luxury good, as the elasticities are always above one (Adeola et al., 2017; Peng et al., 2015). In particular, a rise of 1% in global (national) production increases foreign (national) tourist arrivals at holiday and short-stay accommodations more than hotels (Table 5). The increase in domestic industrial production has a more contained impact on arrivals than foreign industrial production. The Poisson and Negative Binomial models confirm these results (Tables 6 and 7). The unemployment rate, which enters the equations only for domestic arrivals, is significant and negatively related to national tourism flows. An increase of 1% in the rate of change in unemployment rate reduces national arrivals by >1%.

An increase in business confidence, which summarises the expectations of economic operators about their financial conditions, sales and the economy's future, brings about a rise in tourist arrivals at the accommodation (Tables 5-7). Optimistic sentiments influence markets and, thus, the tourism sector. The effect is more prominent for foreign arrivals than national visitors and is more pronounced for hotels than non-hotel accommodations.

A real exchange rate appreciation reduces visitors in hotels and holiday accommodations. The significance and the signs of the coefficients are confirmed across all models. These results suggest that

higher prices lessen arrivals; therefore, price competitiveness is an important factor influencing foreign tourism. This finding corroborates the studies by Munir and Iftikhar (2021) and Tung (2019) among others.

The Infectious Disease Equity Market Volatility Tracker reveals that economic and health-related uncertainty affects more foreign than domestic tourist flows. This finding indicates that health risks due to epidemics and pandemics matter, especially when travelling abroad. Travelling within the national borders also has an impact, but it is less pervasive.

The effect of the *epu* index on domestic tourist arrivals is negative and inelastic. This result is in accordance with Gozgor and Ongan (2017) and İşık et al. (2020). As suggested by Giavazzi and McMahon (2012) and Dragouni et al. (2016), *epu* could directly affect consumer spending behaviour, as households tend to increase their savings and reduce or postpone consumption expenditure (including travels) when policy uncertainty increases. The effect of *epu* on international tourism arrival is instead not always statistically significant but has a positive sign. This result could be explained by the fact that higher uncertainty would cause a fall in domestic output, employment and prices, so that international tourists could benefit from lower prices and, thus, more competitiveness of the selected destination.

The variable associated with virtual museums has a negative sign: it reduces tourist arrivals. The effect is more substantial for foreign than domestic tourists. This result suggests a possible substitution effect between online and offline/in-presence participation. The contraction in terms of tourists due to virtual museums is clearer considering the Negative Binomial models and their estimated marginal effects (Table 8). Specifically, the contraction for the whole sample period with respect to the average value of tourist arrivals is estimated to be 197,708 tourists in Spain and 32,386 tourists in Croatia. Spain and Italy record the highest shrinkage in the number of tourist arrivals for all categories of establishments.

The significance of the variable museum has important implications. It would suggest that online availability of cultural content could facilitate consumers to overcome the obstacles to being on the spot caused, for instance, by health crises, transport costs and time constraints. Moreover, the online channel could allow tourism managers to reach an audience beyond the typical summer seasons. In this context, providing a virtual experience might be useful to de-seasonalise tourism and build

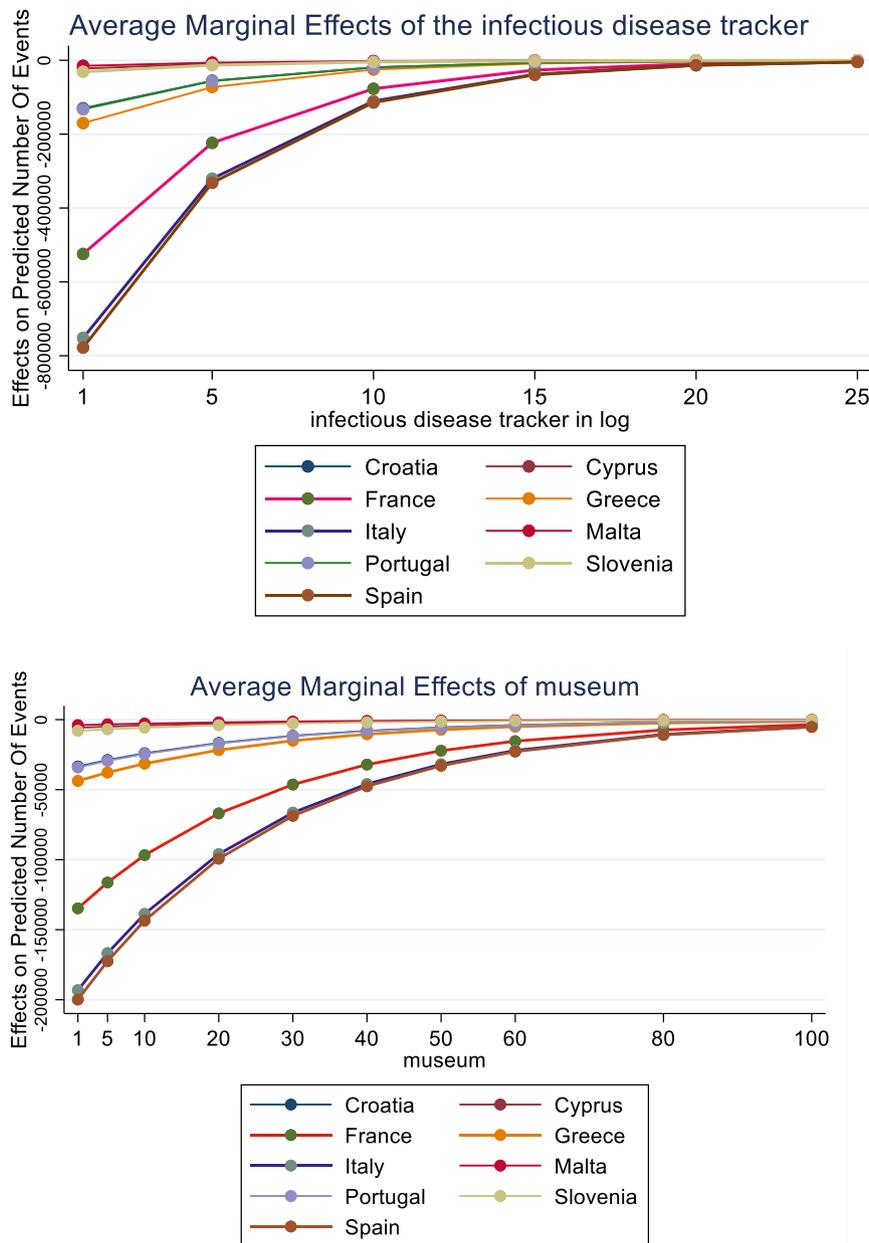


Fig. 4. Marginal effects for Foreign short stay accommodations (Negative Binomial Model).

new strategies for attracting visitors both in the high and low seasons. A suggested strategy for the sector’s managers could be to offer online museum tours for a selection of ‘cultural assets’ in the museum and to reserve the entire museum’s collection for an experience in presence. The incomplete online offer of a ‘cultural asset’ could create further interest in the user and stimulate future in-person attendance. The optimal managerial strategy, hence, would be to blend physical and online museum offers through digital technologies. However, given that not all museums and heritage sites have the optimal technological know-how to provide interactive experiences (Komarac & Ozretić-Došen, 2021), it seems crucial for policy makers to direct public funds to support the digital transition of cultural organisation. For instance, Romolini, Fissi, Gori, and Contri (2020) and Komarac, Ozretić-Došen, and Skare (2017) have documented that many museums in Italy and Croatia have difficulties implementing and maintaining interactive technologies since they depend on limited government financial support.

Fig. 4 reports marginal effects for the Infectious Disease Tracker index and the virtual museum variables in the model, with the number of foreign arrivals at holiday and other short-stay accommodations as dependent variable.

We plot marginal effects for each country for different levels of the explanatory variables. Both plots are similar, with marginal effects relatively flat for Malta, Slovenia and Cyprus and much steeper for France, Italy and Spain. Hence, the latter group of countries is the one affected the most, in terms of tourist arrivals, by the Infectious Disease Equity Market Volatility index and the access to virtual museums.

The pandemic has strongly reduced tourist arrivals across accommodation establishments and countries. The impact has been more substantial for foreign tourism flows than domestic flows. In detail, foreign arrivals have shrunk by 1.1 to 1.2% compared to the non-COVID-19 period. Domestic arrivals have declined by about 0.1–0.2% compared to the non-COVID-19 period (Table 5). The marginal effects of the

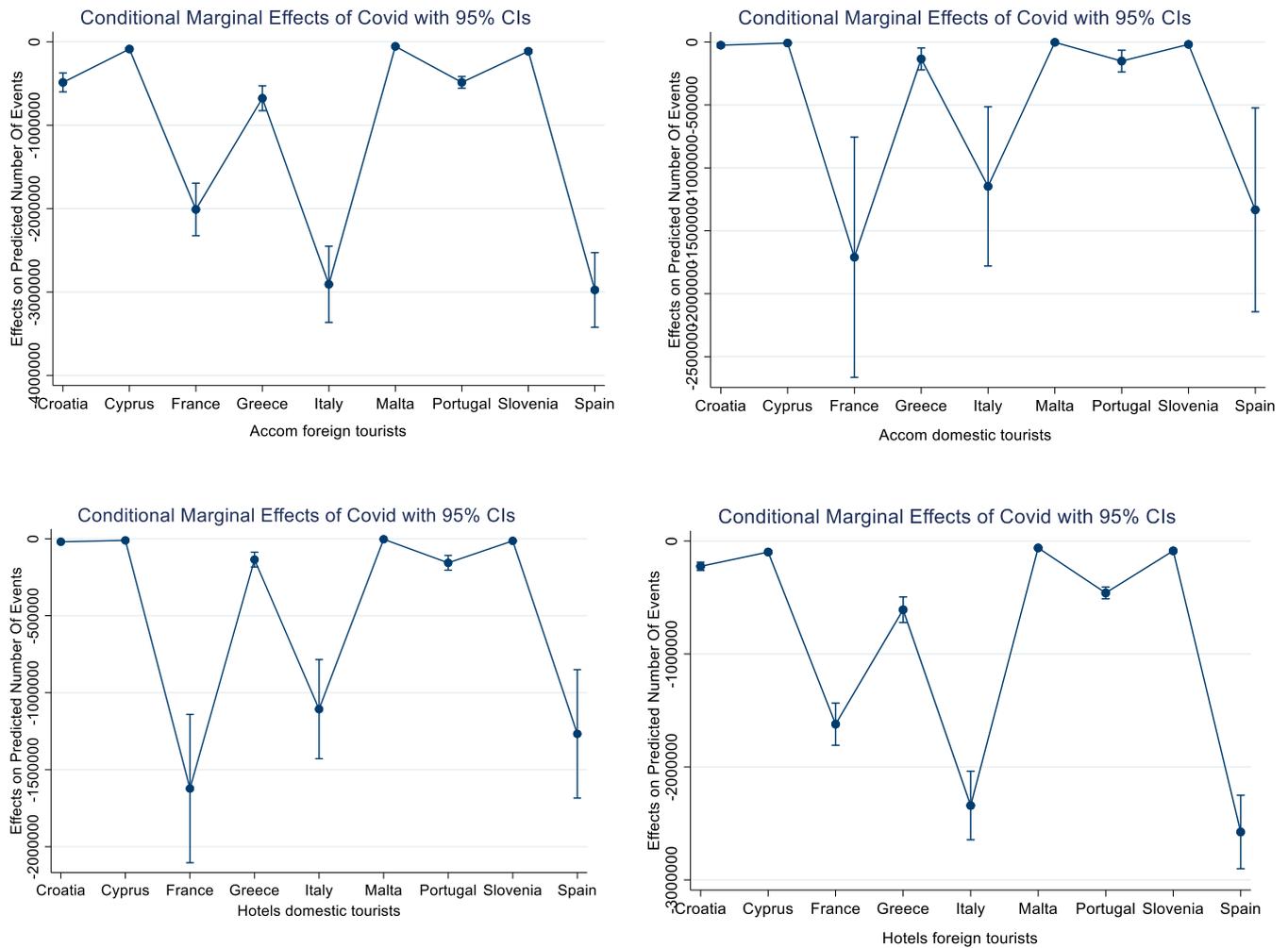


Fig. 5. Marginal effects of COVID-19 (Negative Binomial Model).

Negative Binomial models suggest that the drop in foreign tourist arrivals has been extremely marked for Spain and Italy across all the types of accommodation. Instead, domestic tourist arrivals have recorded a significantly negative impact on France (Table 8). Fig. 5 displays the conditional marginal effects with 95% confidence levels. Again, the effect of COVID-19 has been more severe for Spain and Italy in terms of foreign visitors' contractions, while the drop in domestic tourists has been more substantial for France.

Regarding the country effects, France, Greece, Italy and Spain are able to attract more tourists than Croatia (the reference country) and the other competitors across all the estimated models and specifications (Tables A1-A3, appendix). However, the tourist contraction due to health issues has been more pronounced in Italy, Spain and France.

In synthesis, our results reveal that traditional and new driving channels affect foreign and domestic arrivals. Uncertainty-sentiment factors have an essential role in determining the choice of the destination. The negative effect of COVID-19 has been more prominent for foreign tourists than national tourists and more evident for some countries than others. Countries strongly dependent on the tourism sector and the international tourism market have been the most affected. The search interest for virtual tourism practices also shapes the demand for tourism. Thus, an online supply of tourism experiences could be an interesting solution to manage flows during the out-of-season period or health crises.

### 5. Conclusion

This study has investigated the main drivers of tourist arrivals at establishments for nine EU tourist destinations from January 2010 to March 2022. We have identified traditional and new channels influencing tourism demand and estimated different specifications for foreign and domestic tourist arrivals using fixed effects panel, Poisson and Negative Binomial panel models.

We document that an increase in global industrial production, price competitiveness and labour market condition boost the number of tourist arrivals. Uncertainty-sentiment drivers are fundamental too. A rise in business sentiment increases arrivals, while health-induced market threats or uncertainty, measured by the infectious disease tracker, lessens foreign tourist flows. Economic policy uncertainty leads travellers to postpone their travel plans in periods of market turbulence. As expected, the COVID-19 pandemic has significantly reduced arrivals across countries at different types of establishments. The effect has been more marked for foreign than domestic tourists. The novel variable measuring the interest in online tourism experiences affects tourist arrivals and signals the relevance of behavioural intentions in the choice of travelling.

Despite the usual caveat linked to data availability for some variables, our results suggest that prices and new technologies are relevant tools for tourism. Policies aimed at raising price competitiveness are essential to stimulate consumer choices towards EU tourism destinations. Since virtual tours have enjoyed great popularity during the

pandemic, new technologies could represent an interesting paradigm shift for the tourism industry. They could support tourism resilience during periods of crisis and be very useful in reducing seasonality in periods of economic prosperity. From this perspective, the pandemic crisis can be viewed as an opportunity to improve digitalisation in the tourism industry. For instance, to attract visitors, museum managers should consider offering online tours and providing immersive virtual experiences to appeal to tourists for a visit in-presence in the future. Furthermore, governments could encourage the digital transition of the tourism industry and support the development of digital skills, including big data analysis, data analytics, machine learning and artificial intelligence. Finally, synergic interrelations among the tourism industry, the cultural sector and high-tech companies could help create online programs and initiatives useful also for sustainable tourism. Future research could extend the adoption of our approach (the four-channel demand model) to other regions and countries and develop our Poisson and Negative Binomial models with the panel version of the integer-valued

generalized autoregressive conditional heteroskedastic (INGARCH) models considered, for instance, by Algieri and Leccadito (2021). These models could be useful to deal with the count nature of the dependent variable and with the autocorrelation possibly present in the time series of tourists' arrivals.

**Declaration of Competing Interest**

The authors declare that they have no conflict of interest. There are no financial conflicts of interest to disclose.

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**Appendix A**

**Table A.1**  
Estimated coefficients for the Country Dummy variables in the Fixed-Effect LSDV Panel models.

Panel A						
	(1)	(2)	(3)	(4)	(5)	(6)
	l_acc_foreign	l_acc_foreign	l_acc_foreign	l_acc_nat	l_acc_nat	l_acc_nat
Cyprus	-1.141 *** (0.102)	-1.133 *** (0.103)	-1.153 *** (0.102)	-1.198 *** (0.061)	-1.154 *** (0.062)	-1.193 *** (0.061)
France	2.077 *** (0.103)	2.048 *** (0.102)	2.075 *** (0.103)	4.292 *** (0.061)	4.282 *** (0.061)	4.298 *** (0.061)
Greece	0.540 *** (0.103)	0.566 *** (0.107)	0.518 *** (0.103)	1.504 *** (0.062)	1.578 *** (0.065)	1.510 *** (0.062)
Italy	2.295 *** (0.112)	2.213 *** (0.113)	2.292 *** (0.112)	3.743 *** (0.067)	3.691 *** (0.068)	3.753 *** (0.067)
Malta	-1.528 *** (0.102)	-1.552 *** (0.102)	-1.518 *** (0.102)	-2.203 *** (0.061)	-2.240 *** (0.062)	-2.203 *** (0.061)
Portugal	0.596 *** (0.104)	0.506 *** (0.111)	0.606 *** (0.104)	1.794 *** (0.062)	1.716 *** (0.067)	1.804 *** (0.062)
Slovenia	-0.851 *** (0.102)	-0.913 *** (0.105)	-0.842 *** (0.102)	-0.218 *** (0.061)	-0.268 *** (0.063)	-0.209 *** (0.061)
Spain	2.371 *** (0.112)	2.282 *** (0.115)	2.373 *** (0.112)	3.761 *** (0.067)	3.695 *** (0.069)	3.770 *** (0.067)
Panel B						
	(7)	(8)	(9)	(10)	(11)	(12)
	l_hotel_foreign	l_hotel_foreign	l_hotel_foreign	l_hotel_nat	l_hotel_nat	l_hotel_nat
Cyprus	-0.571 *** (0.091)	-0.578 *** (0.092)	-0.587 *** (0.092)	-0.708 *** (0.055)	-0.674 *** (0.056)	-0.704 *** (0.055)
France	2.369 *** (0.092)	2.343 *** (0.091)	2.364 *** (0.093)	4.472 *** (0.055)	4.465 *** (0.055)	4.477 *** (0.055)
Greece	0.970 *** (0.092)	0.970 *** (0.096)	0.944 *** (0.092)	1.793 *** (0.055)	1.851 *** (0.059)	1.798 *** (0.055)
Italy	2.602 *** (0.100)	2.537 *** (0.102)	2.590 *** (0.101)	3.980 *** (0.060)	3.938 *** (0.062)	3.990 *** (0.060)
Malta	-0.980 *** (0.091)	-0.990 *** (0.092)	-0.970 *** (0.092)	-1.724 *** (0.054)	-1.754 *** (0.056)	-1.724 *** (0.055)
Portugal	1.016 *** (0.093)	0.957 *** (0.099)	1.022 *** (0.093)	2.069 *** (0.056)	2.008 *** (0.060)	2.078 *** (0.056)
Slovenia	-0.605 *** (0.091)	-0.645 *** (0.094)	-0.597 *** (0.092)	-0.329 *** (0.054)	-0.367 *** (0.057)	-0.320 *** (0.055)
Spain	2.716 *** (0.100)	2.651 *** (0.103)	2.712 *** (0.101)	4.010 *** (0.060)	3.958 *** (0.063)	4.019 *** (0.060)

Legend: l\_acc\_foreign = foreign tourist arrivals at holiday and other short-stay accommodation; hotel\_foreign = foreign tourist arrivals at hotels; acc\_nat = national (domestic) tourist arrivals at holiday and other short-stay accommodation; hotel\_nat = national (domestic) tourist arrivals at hotels. Standard errors in parentheses. Asterisks \*\*\*, \*\* and \* denote significance at the 1, 5 and 10% level, i.e. \*p < 0.10, \*\*p < 0.05, \*\*\*p < 0.01.

**Table A.2**  
Estimated coefficients for the Country Dummy variables in the Panel Poisson models.

Panel A						
	(1)	(2)	(3)	(4)	(5)	(6)
	acc_foreign	acc_foreign	acc_foreign	acc_nat	acc_nat	acc_nat
Cyprus	-1.721 *** (0.109)	-1.759 *** (0.109)	-1.723 *** (0.109)	-1.190 *** (0.070)	-1.311 *** (0.089)	-1.178 *** (0.070)
France	1.415 *** (0.107)	1.394 *** (0.106)	1.417 *** (0.107)	4.206 *** (0.055)	4.263 *** (0.063)	4.219 *** (0.055)
Greece	0.333 *** (0.127)	0.269 ** (0.124)	0.329 *** (0.127)	1.700 *** (0.075)	1.551 *** (0.100)	1.667 *** (0.076)
Italy	1.780 *** (0.122)	1.754 *** (0.121)	1.786 *** (0.122)	3.817 *** (0.070)	3.826 *** (0.071)	3.816 *** (0.070)
Malta	-2.181 *** (0.101)	-2.149 *** (0.101)	-2.179 *** (0.101)	-2.488 *** (0.090)	-2.332 *** (0.114)	-2.433 *** (0.090)
Portugal	-0.0091 (0.107)	0.0187 (0.111)	-0.0015 (0.108)	1.789 *** (0.054)	1.830 *** (0.058)	1.793 *** (0.055)
Slovenia	-1.458 *** (0.110)	-1.432 *** (0.112)	-1.453 *** (0.110)	-0.335 *** (0.080)	-0.294 *** (0.080)	-0.297 *** (0.080)
Spain	1.802 *** (0.120)	1.788 *** (0.119)	1.809 *** (0.120)	4.004 *** (0.081)	3.934 *** (0.083)	3.963 *** (0.077)

Panel B						
	(7)	(8)	(9)	(10)	(11)	(12)
	hotel_foreign	hotel_foreign	hotel_foreign	hotel_nat	hotel_nat	hotel_nat
Cyprus	-0.828 *** (0.081)	-0.871 *** (0.082)	-0.832 *** (0.081)	-0.633 *** (0.061)	-0.799 *** (0.075)	-0.736 *** (0.074)
France	1.979 *** (0.072)	1.956 *** (0.072)	1.981 *** (0.072)	4.402 *** (0.034)	4.471 *** (0.043)	4.476 *** (0.031)
Greece	1.007 *** (0.100)	0.933 *** (0.097)	1.000 *** (0.100)	1.945 *** (0.050)	1.762 *** (0.073)	1.784 *** (0.041)
Italy	2.339 *** (0.091)	2.316 *** (0.090)	2.348 *** (0.091)	4.026 *** (0.051)	4.041 *** (0.053)	4.036 *** (0.051)
Malta	-1.311 *** (0.069)	-1.274 *** (0.070)	-1.308 *** (0.069)	-1.898 *** (0.068)	-1.719 *** (0.090)	-1.700 *** (0.045)
Portugal	0.709 *** (0.076)	0.742 *** (0.080)	0.720 *** (0.076)	2.066 *** (0.036)	2.119 *** (0.041)	2.108 *** (0.038)
Slovenia	-0.954 *** (0.071)	-0.927 *** (0.074)	-0.949 *** (0.071)	-0.386 *** (0.059)	-0.347 *** (0.059)	-0.306 *** (0.049)
Spain	2.432 *** (0.090)	2.424 *** (0.090)	2.444 *** (0.090)	4.187 *** (0.057)	4.116 *** (0.062)	4.079 *** (0.048)

Legend: *acc\_foreign* = foreign tourist arrivals at holiday and other short-stay accommodation; *hotel\_foreign* = foreign tourist arrivals at hotels; *acc\_nat* = national (domestic) tourist arrivals at holiday and other short-stay accommodation; *hotel\_nat* = national (domestic) tourist arrivals at hotels. Standard errors in parentheses. Asterisks \*\*\*, \*\* and \* denote significance at the 1, 5 and 10% level, i.e. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

**Table A.3**  
Estimated coefficients for the Country Dummy variables in the Negative Binomial Panel models.

Panel A						
	(1)	(2)	(3)	(4)	(5)	(6)
	acc_foreign	acc_foreign	acc_foreign	acc_nat	acc_nat	acc_nat
Cyprus	-1.714 *** (0.120)	-1.706 *** (0.122)	-1.717 *** (0.120)	-1.166 *** (0.068)	-1.331 *** (0.069)	-1.160 *** (0.069)
France	1.364 *** (0.118)	1.353 *** (0.118)	1.364 *** (0.118)	4.187 *** (0.056)	4.226 *** (0.059)	4.196 *** (0.056)
Greece	0.367 *** (0.138)	0.369 *** (0.141)	0.356 *** (0.137)	1.756 *** (0.067)	1.588 *** (0.077)	1.736 *** (0.067)
Italy	1.610 *** (0.125)	1.571 *** (0.125)	1.614 *** (0.125)	3.716 *** (0.068)	3.703 *** (0.069)	3.724 *** (0.068)
Malta	-2.236 *** (0.112)	-2.236 *** (0.112)	-2.229 *** (0.111)	-2.500 *** (0.079)	-2.364 *** (0.092)	-2.470 *** (0.078)
Portugal	-0.130 (0.114)	-0.168 (0.119)	-0.118 (0.114)	1.734 *** (0.053)	1.767 *** (0.056)	1.742 *** (0.054)
Slovenia	-1.466 *** (0.122)	-1.495 *** (0.122)	-1.456 *** (0.122)	-0.333 *** (0.072)	-0.326 *** (0.073)	-0.312 *** (0.072)
Spain	1.627 *** (0.118)	1.586 *** (0.120)	1.634 *** (0.118)	3.930 *** (0.066)	3.864 *** (0.068)	3.918 *** (0.065)

(continued on next page)

Table A.3 (continued)

Panel A						
	(1)	(2)	(3)	(4)	(5)	(6)
	acc_foreign	acc_foreign	acc_foreign	acc_nat	acc_nat	acc_nat
Panel B						
	(7)	(8)	(9)	(10)	(11)	(12)
	hotel_foreign	hotel_foreign	hotel_foreign	hotel_nat	hotel_nat	hotel_nat
Cyprus	-0.779 *** (0.090)	-0.783 *** (0.091)	-0.785 *** (0.090)	-0.611 *** (0.061)	-0.805 *** (0.061)	-0.734 *** (0.060)
France	1.965 *** (0.082)	1.948 *** (0.081)	1.965 *** (0.082)	4.399 *** (0.039)	4.450 *** (0.042)	4.481 *** (0.034)
Greece	1.098 *** (0.110)	1.077 *** (0.111)	1.082 *** (0.109)	1.979 *** (0.046)	1.790 *** (0.059)	1.803 *** (0.043)
Italy	2.238 *** (0.094)	2.194 *** (0.094)	2.242 *** (0.094)	3.983 *** (0.055)	3.974 *** (0.056)	3.995 *** (0.054)
Malta	-1.321 *** (0.081)	-1.321 *** (0.080)	-1.312 *** (0.081)	-1.892 *** (0.068)	-1.730 *** (0.081)	-1.672 *** (0.047)
Portugal	0.643 *** (0.082)	0.606 *** (0.088)	0.658 *** (0.082)	2.041 *** (0.039)	2.086 *** (0.042)	2.092 *** (0.039)
Slovenia	-0.944 *** (0.082)	-0.972 *** (0.083)	-0.932 *** (0.082)	-0.380 *** (0.056)	-0.366 *** (0.056)	-0.299 *** (0.043)
Spain	2.326 *** (0.089)	2.282 *** (0.091)	2.334 *** (0.088)	4.161 *** (0.054)	4.090 *** (0.055)	4.047 *** (0.046)

Legend: *acc\_foreign* = foreign tourist arrivals at holiday and other short-stay accommodation; *hotel\_foreign* = foreign tourist arrivals at hotels; *acc\_nat* = national (domestic) tourist arrivals at holiday and other short-stay accommodation; *hotel\_nat* = national (domestic) tourist arrivals at hotels. Standard errors in parentheses. Asterisks \*\*\*, \*\* and \* denote significance at the 1, 5 and 10% level, i.e. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

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