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Estimating the dynamic effects of volcano eruptions on domestic tourism: Evidence based on mobile-phone geo-positioning records

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Abstract:

Despite volcanic eruptions are among the most detrimental phenomena for tourism activities, few studies have explored their effects on tourism arrivals. This study investigates the dynamic effects of *Cumbre Vieja* eruption (La Palma Island, Spain) on domestic tourism demand at the municipal level. By exploring mobile-phone geo-position data in a quasi-experimental setting, we analyse the variation in *local, peninsular* and *domestic* tourists in La Palma municipalities as compared to non-treated municipalities in other islands in the Canary Archipelago after the eruption. Our event study estimates point to an average drop of about 41% in domestic tourism during the eruption, with a further decrease of around 55% in the following four months. Our findings offer valuable insights about island tourism-dependent economies' resilience to natural disasters.

Keywords: Natural hazards; Volcanic Eruption; Dynamic effects; Tourism arrivals; Panel event study.

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1. INTRODUCTION

The increasing frequency of natural disasters in recent years, largely attributed to climate change, poses significant threats to human well-being and ecosystems (IPCC, 2022). For island economies with a high endowment of natural resources, the tourism sector is nowadays a major engine of socio-economic development (Seetanah, 2011). Indeed, recent works show that the economic contribution of the tourism industry to per capita income and employment growth differs between island and mainland destinations because islands are relatively more damaged by tourism demand concentration, overtourism and environmental degradation (Mazzola et al., 2022). The low degree of diversification and high dependence on tourism inflows of island economies make them highly exposed to natural hazards (Coulson et al., 2020), which exacerbates the intrinsic vulnerabilities of the tourism industry (Meheux & Parker 2006).

In the aftermath of a natural disaster, the number of visitors to affected areas is likely to decrease for different reasons. On the one hand, disruptive events might provoke severe damages to public infrastructures and tourism facilities, thereby worsening destination accessibility and preventing participation in tourism activities (Becken et al., 2014). On the other hand, people might become reluctant to visit destinations that are highly exposed to natural disasters because of risk avoidance mechanisms (Çakar, 2021; Lehto et al., 2008; Park & Reisinger, 2010; Walters et al., 2015).¹ In this regard, the media might aggravate the negative effects of natural disasters, further increasing risk perceptions among tourists (Walters et al., 2016).

Several works have explored the effects of natural events on tourism-led economies by looking at different types of hazards like earthquakes (Cheng & Zhang, 2020; Mazzocchi & Motini, 2001; Huan & Min, 2002; Yang et al., 2011), hurricanes (Kim & Marcouiller, 2015), tropical storms (Schmude et al., 2018), forest fires (Hystad & Keller, 2008), bushfires (Pyke et al., 2016), typhoons (Tsai et al., 2016) or tsunamis (Barbhuiya & Chatterjee, 2020). Using data for 177 countries between 1995 and 2018, Lan et al. (2021) document that the severity of natural disasters in terms of the number of deaths negatively impacts inbound tourism; however, the frequency of disasters exerts a positive effect. Rossello et al. (2020) offer a global analysis of

¹ The destination image of destinations is heavily damaged after natural hazards (Pearlman & Melnik, 2008; Wu & Shimizu, 2020).

the effects of different types of natural disasters on international tourism, showing that volcanic eruptions emerge as the most deterring events for tourism flows.²

Surprisingly, scarce attention has been devoted yet to the analysis of the effects of volcanic activity on the tourism sector. Medeiros et al. (2021) perform a simulation analysis of the potential effects of two types of eruptions (characterized by a different degree of severity) in the Portuguese Azores archipelago. Under the total-destruction scenario, the overall economic loss is estimated to be of about 145 million euros. However, the authors mostly focus on direct damages; more specifically, they evaluate the direct effect of the eruption on hotel buildings and deduce the overall revenue loss of the accommodation units. In a recent work, Leoni and Boto-García (2022) analyse the effect of *Cumbre Vieja* (La Palma Island, Spain) volcano eruption in September 2021 on the tourism sector of the Canary Archipelago.³ Their work jointly examines the short-term effects of the volcano eruption on international demand, hotel labour demand and tourism supply (number of open hotels). Using a difference-in-differences approach, the authors find evidence of an asymmetric decline in the three outcomes, during and after the volcanic eruption. In particular, foreign demand in La Palma Island decreased by 76.7 percentage points (hereafter pp) during the eruption and 64.55 pp afterwards as compared to non-treated areas. Moreover, this study finds no evidence of spillover effects on neighbouring islands.

The current work builds upon Leoni and Boto-García (2022) by studying a distinct facet of La Palma volcano eruption: the dynamic effects of the eruption on the inflow of domestic tourists at the municipality level. In this respect, Barbhuiya & Chatterjee (2020) document that domestic and international tourists react differently to natural disasters. We specifically distinguish between local tourists (citizens residing in the Canary Archipelago) and what we label as 'peninsular' tourists (those living in any other Spanish region). We are particularly interested in uncovering potential differences in the resilience of both segments that could be associated to their distinct risk aversion based on their place of living. Whereas Spanish tourists from the rest of Spain might be highly discouraged by volcanic risk, local tourists that already live in a volcanic environment might be less sensitive to the risk of further eruptions. In this respect, a

² Aside from their effects on tourism flows, volcanos are among the most worrying natural disasters for public health. Halliday et al. (2019) show that a marginal increase in particulates emission from volcano eruptions produce significant increases in expenditures on emergency room visits for pulmonar outcomes.

³ Relatedly, Pérez-Granja et al. (2022) investigate the effects of the volcano on tourists' expenditure in the Canary Islands. They document increases in overall expenditure and per category following the eruption, which is interpreted in terms of prosocial consumption.

recent work by Jiménez-Barreto et al. (2022) shows that residents in La Palma expressed a strong 'fresh start mindset' that is linked to greater support for tourism activities after the natural disaster, which better evaluations of the positive impacts of tourism and less concern about its negative externalities.

For this purpose, we exploit a rich monthly panel dataset of the number of local and peninsular tourists visiting the Canary Islands during the period between August 2020 and July 2022, disaggregated at the municipality level. Therefore, the study period includes one year preceding and one year following the eruption. Data are collected based on mobile phones geographical position tracking. From a methodological viewpoint, we estimate a panel event-study model (Clarke & Tapia-Schythe, 2021) that allows us to evaluate the temporal dynamics of tourism demand following the eruption. Since the number of tourists that a municipality receives is likely to vary depending on its economic development and sociodemographic composition, our econometric specification includes a full set of period and municipality fixed effects. Our results point to a significant drop in both local and peninsular tourism demand after the event. Importantly, the decline is found to be persistent throughout the post-eruption period.

The current work contributes to the existing literature on the effects of natural hazards on tourism demand in different ways. Firstly, a proper understanding of how natural disasters in general and volcanic eruptions in particular affect tourism flows is still a research gap in the existing literature. Policy makers and destination managers can use this information for disaster planning management and to develop adaptation policies and interventions aimed at battling climate change effects (Calgaro et al., 2014; Jopp et al., 2010; Ritchie, 2008; Seraphin, 2019). We aim to expand the evidence on the topic by examining the resilience exhibited by La Palma Island to the shock. From this viewpoint, the recovery trajectories followed by tourist areas after natural disasters are a topic of great interest for scholars and policy makers (Bangwayo-Skeete & Skeete, 2021; Cheng & Zhang, 2020; Filimonau & De Coteau, 2020; Tsai et al., 2016). Secondly, while Leoni and Boto-García (2022) focus on international tourism demand, we add novel evidence on how local and peninsular tourism flows react to volcano eruptions. Despite constituting a significant portion of total demand, domestic has often been undervalued and overlooked in previous research. As abovementioned, this allows us to inspect potential heterogeneous responses associated to tourists' risk aversion based on the place of origin. Thirdly, in contrast to Leoni and Boto-García (2022) that analysed data about hotel demand in eight tourist zones of the Canary Islands, we work on total tourists (including those visiting friends and relatives) at the municipality level. Such dataset offers the possibility to conduct a more fine-grained examination of the phenomenon.

The rest of the article is organized as follows. Section 2 offers a description of the case study and the timeline of the volcanic event. Section 3 discusses the data and presents a detailed descriptive analysis of tourism arrivals over time and across municipalities together with their main correlates. Section 4 explains the methodology and the research design used for the empirical analysis. Section 5 presents and discusses the estimation results. Finally, Section 6 ends with some concluding remarks, limitations, and an outlook for future research.

2. CASE STUDY

The study area is the Spanish Canary Archipelago, composed by eight main islands (Tenerife, Fuerteventura, Gran Canaria, Lanzarote, La Palma, La Gomera, El Hierro and La Graciosa) and several small islets, located in the Macronesian tropical region. Thanks to their geographical position, the islands enjoy a mild climate all year round which has favoured the booming of the tourism activity, hosting about 10 million tourists per year (INE, 2022).

Together with agricultural production, tourism represents one of the main economic activities of La Palma Island. Starting its development in late 80s, La Palma developed a tourism model that is quite different from the mass tourism that characterizes other islands in the archipelago like Tenerife or Lanzarote. According to official statistics from La Palma Island Council, the island has approximately 16,000 bed places, which rise to about 20,000 if non-official holiday homes are included (Ramos-Pérez, 2022).

The event object of the current work is the volcanic eruption of *Cumbre Vieja* (La Palma Island), which took place on September 19th, 2021, and lasted for 86 days.⁴ The area is under the status of UNESCO biosphere reserve and includes two volcanic centres (the older *Caldera Taburiente* and the younger *Cumbre Vieja*) that are the most active volcanoes in the archipelago. Although fortunately the recent volcano activity did not produce casualties, it is considered the most destructive in the last century in Europe; it produced significant damage to properties and infrastructure in the area of around 10 km² where the lava flowed. During the eruption, water quality was seriously worsened, with a markedly increased turbidity due to the

⁴ The reader is referred to Martí et al. (2022) for details about the geological setting, timing, areas affected and characteristics of the affected area.

deposition of volcanic ash and other materials (Caballero et al., 2022). Similarly, local air quality was heavily compromised, with the presence of sulphate and dust aerosols in the atmosphere (Filonchyk et al., 2022). The eruption destroyed 3,000 buildings, with several tourism accommodations becoming inoperable due to structural damages. According to the local government, the total damage was estimated at approximately EUR 843 million.

3. DATA

3.1.Dataset on domestic tourism flows

We use monthly data on the number of domestic (Spanish) tourists visiting the Canary Islands during the period August 2020 and July 2022 at the municipality level (n=88). We select this time span to avoid the break in the series associated to the COVID-19 lockdown that took place in Spain between March and June 2020. We nevertheless have one full year before the eruption (August 2020-August 2021) and 11 months after it (September 2021-July 2022), hence guaranteeing the same degree of representativeness of pre- and post-event periods.

The data is drawn from the experimental statistics of the Spanish National Statistics Institute (INE), which estimates the total number of domestic tourists in a given municipality during a month based on daily mobile phone tracking.⁵ In particular, daily mobility records are obtained thanks to an agreement with the three main mobile phone operators based on anonymised, population-aggregated geo-positioning data.⁶ The area of residence of an individual is determined according to the place where the phone is observed most of the time between 0:00 and 6:00 considering a 60-day period. The owner of the phone is deemed a 'tourist' if the mobile phone is observed most of the time between 22:00 and 6:00 in a municipality different from the place of residence and is also observed there after 6:00 AM the following day (implying at least an overnight stay away from home).⁷

⁵ Domestic tourists are typically measured using household surveys. In Spain, the Domestic Travel Survey asks Spanish residents about their tourist trips; based on that, aggregate level statistics are obtained. The use of mobile geo-positioning data complements that as it allows to get more granular information at the municipality level.

⁶ The data comes from Movistar, Orange and Vodafone, which represent around 79% of the mobile phone market in Spain (National Commission for Markets and Competence, 2019).

⁷ The dataset is available at: <u>https://www.ine.es/dynt3/inebase/es/index.htm?padre=8578&capsel=8581</u>

Although this data could be potentially affected by measurement error at the municipalities' border, it offers the advantage of capturing all types of tourism. That is, we use a broad definition of tourism that considers trips related to leisure, business, as well as visiting friends & relatives. Data on domestic tourism is typically obtained from official records for hotels (Boto-García & Mayor, 2022), which neglect other forms of accommodation, or survey microdata (Boto-García & Leoni, 2021), which focus on the main destination and depend on respondents' accuracy in outlining their travel route. From this viewpoint, smartphone movement data can be a more reliable source of information about spatial-temporal flows (Couture et al., 2022).

Since the area of residence of each mobile phone is known, INE decomposes the number of tourists that stay at each municipality per province of origin. Based on this, we distinguish between peninsular (domestic tourists travelling from the rest of Spain, including the Balearic Islands) and local (domestic tourists travelling within the Canary Islands) tourists. By using this approach, we can assess the potential distinct response of both groups to the volcano eruption.

3.2.Descriptive analysis

Table 1 presents descriptive statistics of the total domestic tourists and disaggregated by origin (peninsular and local) in the pre- and post-eruption periods. On average, municipalities in the Canary Islands received 2,267 domestic tourists. Out of them, around 69% come from the rest of Spanish regions and the remaining 31% from other municipalities in the Islands. Nonetheless, the large standard deviation suggests the existence of important heterogeneity across municipalities. The mean number of tourists is greater in the post-eruption period in both the peninsular and local segments. This is likely explained by the overall increase in tourism demand by the beginning of 2020 following the end of all COVID-19 related travel restrictions and the smooth increase in vaccination rates across the country.⁸

⁸ Using microdata for the summer of 2021, Boto-García and Baños-Pino (2022) show that vaccination against COVID-19 propelled the willingness to travel through a lower risk aversion to get infected mechanism.

All sample	Mean	SD	Min	Max
Domestic tourists	2,266.79	4,347.56	0	36,037
Peninsular tourists	1,560.36	3,146.48	0	28,581
Local tourists	764.46	1,470.41	30	14,719
Pre-eruption	Mean	SD	Min	Max
Domestic tourists	1,737.76	3,294.55	0	28,590
Peninsular tourists	1,136.63	2,295.48	0	17,584
Local tourists	648.84	1,205.29	30	11,006
Post-eruption	Mean	SD	Min	Max
Domestic tourists	2,793.82	5,137.03	0	36,017
Peninsular tourists	1,980.79	3,761.62	4	28,581
Local tourists	879.17	1,685.71	31	14,719

Table 1. Summary statistics of domestic, peninsular and local tourists considering the full sample and also distinguishing between pre- and post-eruption periods

Figures 1, 2 and 3 map the mean values of the three measures of domestic tourism per municipality before and after the eruption. We get three main insights from these maps: 1) there are notable differences in the inflow of tourists over the territory, with the islands of Fuerteventura and Lanzarote and some municipalities of Gran Canaria and Tenerife islands concentrating the largest shares of visitors; 2) the geographical distribution of local and peninsular tourists is fairly similar; and 3) aside from the overall level change between pre- and post-eruption periods, it seems that the differences in peninsular and local demand among municipalities remain about the same before and after the eruption.



Figure 1. Mean number of domestic tourists in the pre- (Sept. 2020-August 2021) and post-eruption (Sept. 2021-July 2022) periods per municipality.



Figure 2. Mean number of peninsular tourists in the pre- (Sept. 2020-August 2021) and post-eruption (Sept. 2021-July 2022) periods per municipality.



Figure 3. Mean number of local tourists in the pre- (Sept. 2020-August 2021) and post-eruption (Sept. 2021-July 2022) periods per municipality.

Figure 4 plots the series of total domestic (Panel A), peninsular (Panel B) and local (Panel C) tourists in the sample period for each of the 88 municipalities (in logs), distinguishing between treated (municipalities located in La Palma Island) and non-treated units (the other islands).⁹ We see that domestic tourism in La Palma is lower than in the rest of the Canaries; nonetheless, there are relevant level differences within the island. Visually, we can see a drop in demand around the eruption timing, although this could be also due to the overlapping with the end of the summer season. Interestingly, the plots for peninsular and local tourists are quite similar, suggesting that the demand of both segments evolves in parallel.

⁹ Because there are relevant scale differences across municipalities, we take the natural logs to smooth and visually compare them.



Figure 4. Time evolution of total (Panel A), peninsular (Panel B) and local (Panel C) domestic tourists (in logs)

3.3.Municipality controls

The number of tourists a municipality receives is likely to vary depending on its economic development and sociodemographic composition. We collect monthly municipality-level data about the following variables as potential controls: 1) overall number of employed people, 2) number of employed people in the hospitality sector, 3) number of registered firms, 4) population size, 5) average age of the population, and 6) migratory balance, obtained as the difference between people entering (immigrants) and leaving (emigrants) the municipality. The data is provided by the Canary Institute of Statistics (ISCAT) based on several different sources.¹⁰ Table 2 presents summary statistics of the above-mentioned variables.

Municipalities in the Canary Islands have about 9,600 workers, out of which 1,500 are employed in the hospitality sector. On average, municipalities have around 700 firms, 24,700 inhabitants of 44 years of age and a positive migratory balance of 181 people. With the purpose of describing the relationship between domestic tourism demand and the characteristics of the municipality, Figures 5 and 6 present binned scatterplots of the pairwise relationship between total domestic tourism flows and each of the municipality controls considered (all in logs except the migratory balance) considering the pre-treatment period only. We see that domestic demand is positively correlated with the number of workers, population size, the number of firms and the migratory balance; nonetheless; demand is inversely related to average age. Descriptive OLS regressions of the three tourism demand measures on these variables indicate demand is highly correlated with employment in general and in the sector (Table 3).¹¹ Peninsular demand seems to be inversely related to average age whereas the opposite applies in the case of local demand.

¹⁰ The data can be accessed at:

https://www3.gobiernodecanarias.org/istac/indicators-visualizations/indicatorsSystems/C00067A.html ¹¹ Population size is not included in these regression as it is highly correlated with most municipality characteristics.

Variable	Definition	Source	Mean	SD	Min	Max
Employed	Number of people registered as employed the last day of each quarter	Social Security	9,662.83	25,854.8	119	201,807
Employed_hospitality	Number of people registered as employed in the hospitality sector the last day of each quarter	Social Security	1,510.72	3,058.12	19	18,439
Firms	Number of registered firms the last day of the month	Social Security	701.77	1,500.88	13	11,529
Population	Number of people in the municipality (1st January)	Municipal Population Census	24,699.67	49,318.92	762	381,223
Av. Age	Average age of the people living in the municipality (1 st January)	Municipal Population Census	43.98	3.21	37.2	51.9
Mig. Balance	Difference between new residents (immigrants) and leaving population (emigrants)	Municipal Population Census	181.31	455.47	-667	3,497

Table 2. Descriptive statistics of the municipality controls

Table 3. Descriptive OLS regression of domestic demand on municipality characteristics (pre-treatment period)

	(1)	(2)	(3)
	Log domestic	Log peninsular	Log local
	tourists	tourists	tourists
Log employed_hospitality	0.442***	0.569***	0.155***
	(0.032)	(0.034)	(0.035)
Log Employed	0.579***	0.509***	0.833***
	(0.104)	(0.110)	(0.115)
Log Firms	-0.219*	-0.228*	-0.301**
	(0.113)	(0.118)	(0.124)
Log Av. Age	0.300	-1.698***	1.916***
	(0.442)	(0.468)	(0.489)
Mig. Balance	9.9e-05	1.4e-04**	7.1e-05
	(6.6e-05)	(7.0e-05)	(7.3e-05)
Constant	-0.708	6.004***	-7.473***
	(1.839)	(1.946)	(2.035)
Observations	1,034	1,008	1,009
R-squared	0.760	0.797	0.622

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1



Figure 5. Binned scatterplot of the relationship between domestic tourists and the municipality controls (in logs except migratory balance) (I)



Figure 6. Binned scatterplot of the relationship between domestic tourists and the municipality controls (in logs except migratory balance) (II)

4. EMPIRICAL STRATEGY

Our goal is to evaluate the dynamic treatment effects of the volcano eruption on the number of domestic tourists. Let $Post_t$ denote a binary indicator that takes value 1 from the period when *Cumbre Vieja* volcano erupted (September 2021) onwards and 0 otherwise. Let $Treated_m$ be another binary indicator for municipalities located in La Palma Island (treated units) and 0 otherwise.¹² Since we observe the outcomes (tourism demand) for treated and non-treated municipalities before and after the eruption, we have a difference-in-differences research design in which the Average Treatment Effect on the Treated (ATT) would be given by the coefficient of the interaction between $Treated_m$ and $Post_t$ from a linear two-way fixed effects regression.¹³

However, the static DiD model could produce misleading estimates in situations where the effect of the event is non-constant over time.¹⁴ To allow for further flexibility in the time pattern of the treatment effect, we propose a panel event study specification (Clarke & Tapia-Schythe, 2021) with leads and lags of a binary indicator for the eruption in treated municipalities (*Treated*_m × *Post*_t) as follows:

$$\ln Y_{mt} = \alpha + \sum_{j=2}^{J} \beta_j \left(Lead \, j \right)_{mt} + \sum_{k=1}^{K} \gamma_j \left(Lag \, k \right)_{mt} + \mu_m + \delta_t + \varepsilon_{mt} \tag{1}$$

where Y_{mt} represent the log of the number of domestic tourists in municipality m (for m = 1, ..., M) in period t (for t = 1, ..., T), μ_m and δ_t are municipality and period fixed effects, respectively, and ε_{mt} is the error term.

Since the eruption takes place at t=14 for all the treated municipalities (sharp design), the leads and lags for $Treated_m \times Post_t$ are formally defined as follows:

¹² The control group is composed of all the municipalities located in any of the islands in the Canary Archipelago other than La Palma. Although it could be argued that their consideration as the control group could violate the SUTVA assumption needed for causal inference through spillover effects, Leoni & Boto-García (2022) show that neither international tourism demand, hotel supply or the number of hired workers in the neighbouring islands of Tenerife and La Gomera have been affected by the volcano. The use of other municipalities in mainland Spain or the Balearic Islands as the control group would be more problematic given the important differences in seasonality (e.g., Duro, 2016).

¹³ The DiD estimand as given by such coefficient would reflect the average difference in demand between treated and non-treated municipalities before and after.

¹⁴ Note that because we have a sharp design in which all the units in the treatment group become treated at the same period, we do not envisage concerns regarding the negative weighting issue (Goodman-Bacon, 2021).

$$(Lead J)_{mt} = 1 if (t \le 14 - J)$$

 $(Lead j)_{mt} = 1 if (t = 14 - j)$
 $(Lag k)_{mt} = 1 if (t = 14 + k)$
 $(Lag K)_{mt} = 1 if (t \ge 14 + K)$

The lags refer to how many periods have elapsed since the volcano eruption and capture the intended dynamic treatment effects. On the contrary, the leads indicate how many periods remain until the volcano eruption and capture potential anticipation effects and/or non-parallel trends between treated and non-treated municipalities.¹⁵ The leads and lags can be seen as interactions between the treatment dummy and the period fixed effects. For causal inference, it is therefore compulsory that none of the leads are statistically significant (i.e., everything else being equal, there are no systematic differences in outcomes between municipalities in La Palma Island and the rest).¹⁶ Although this does not guarantee that treated and non-treated units would have evolved in parallel in the absence of the volcano, if trends are parallel before, we could expect them to also evolve in parallel afterwards. The first lead is omitted to capture the baseline difference between treated and non-treated municipalities without the eruption, and that is why *j* starts at 2. We consider K = J = 7 so that leads and lags beyond 7 periods are accumulated in Lead 7 and Lag 7.

Because the volcano erupted in September 2021 (at the end of the summer period), one threat to identification is that demand could decline at a faster rate in La Palma Island than in the rest of islands after the summer period (in the absence of the eruption). If this were the case, our estimates could be downward biased. Note this could happen even if treated and non-treated units follow parallel trends (on average) before the eruption (spring and summer). To account for this potential issue, we allow for a linear trend in event time. As such, the estimates for the lags measure the change in tourism demand in each segment following the eruption relative to an extrapolated linear trend. This modelling strategy closely follows Dobkin et al. (2018) and the reader is referred to Freyaldenhoven et al. (2021) for further details on this methodological matter.

¹⁵ As discussed in Clarke & Tapia-Schythe (2021) there are different alternative parametrizations of the panel event study. We closely follow the one presented by these authors.

¹⁶ Leoni & Boto-Garcia (2022) do not detect evidence against the parallel trend assumption in international tourism between treated (municipalities in La Palma) and non-treated areas (rest of the Canaries) before the eruption event.

For our primary analysis, we estimate a model without covariates so that the empirical specification is a dynamic version of a two-way fixed effects linear panel regression. The rationale behind this decision is that the inclusion of time-varying controls (e.g., employment level) could lead to identification problems and misleading estimates because they are plausibly endogenous (Caetano et al., 2022). Similarly, we do not consider other almost time-invariant controls, like population, number of firms, average age or the migratory balance; instead, we control for municipality heterogeneity through a full set of municipality fixed effects. As regards the outcome of interest, we run separate regressions for local visitors (those living in the Canary Islands), the number of peninsular visitors (those living in the Spanish mainland and the Balearic Islands) and the pool of domestic visitors (which includes both).

5. RESULTS

Table 4 presents the coefficient estimates for the model in (1). To ensure an easier interpretation of the log-linear estimates, Table 5 reports the percentage variation of the number of tourists using the transformation proposed by Halvorsen and Palmquist (1980). Figures 7-9 plot the estimates of the event study dummies in Table 4 along with their corresponding 95% confidence intervals for the three different outcomes (relative to the pre-event trend). As expected, the event study lags point to a significant drop in tourism inflows to municipalities in La Palma Island after the volcano eruption as compared to contemporaneous values in the other islands. On average, we estimate a decrease of around 41 percentage points (hereafter pp) in total domestic flows during the eruption period.¹⁷ Interestingly, such decrease is stronger for local tourists (-46 pp) than for peninsular tourists (-39 pp).

The drop is comparatively reduced in the eruption month (September 2021) and even nonsignificant for peninsular tourists. This is kind of expected given that the eruption took place on 19th September; by that period, La Palma Island had already registered a high level of tourism inflows. Looking at the far distant event study lags referring to the post-eruption period (lags 4 to 7), we see that domestic tourism declined quantitatively more than during the eruption period. Again, the drop appears to be greater for local (-60 pp) than for peninsular tourists (-54 pp).

The distinct drops in flows between local tourists and those coming from other regions in Spain during and post eruption deserve further discussion. In line with Barbhuiya & Chatterjee (2020),

¹⁷ This has been computed as a simple average of the coefficients of the event time lags 0 to 3 (inclusive).

we document that tourism demand reaction to natural disasters varies depending on the place of origin. We would expect local tourists to be less deterred by travelling within the Archipelago than peninsular ones because of being more tolerant to volcanic risk. On the contrary, our estimates point to demand from the rest of Spain being more resilient to the shock. We envisage at least two complementary explanations for this pattern.

	(1)	(2)	(3)
Variables	Log Domestic	Log peninsular	Log local tourists
	tourists	tourists	
Lead 7	0.240*	0.295**	0.247*
	(0.123)	(0.138)	(0.138)
Lead 6	0.106*	0.083	0.140**
	(0.057)	(0.064)	(0.064)
Lead 5	0.036	-0.021	0.089
	(0.088)	(0.098)	(0.098)
Lead 4	-0.059	-0.025	-0.102
	(0.104)	(0.116)	(0.116)
Lead 3	-0.204*	-0.128	-0.190
	(0.113)	(0.128)	(0.129)
Lead 2	0.012	-0.067	0.077
	(0.104)	(0.116)	(0.116)
Lag 0	-0.307**	-0.171	-0.454***
	(0.127)	(0.140)	(0.141)
Lag 1	-0.745***	-0.754***	-0.801***
-	(0.143)	(0.160)	(0.161)
Lag 2	-0.578***	-0.591***	-0.671***
-	(0.162)	(0.180)	(0.180)
Lag 3	-0.538***	-0.558***	-0.605***
-	(0.183)	(0.203)	(0.203)
Lag 4	-0.744***	-0.769***	-0.798***
	(0.204)	(0.227)	(0.227)
Lag 5	-0.859***	-0.948***	-0.884***
-	(0.227)	(0.252)	(0.253)
Lag 6	-0.866***	-0.881***	-0.955***
0	(0.249)	(0.278)	(0.279)
Lag 7	-0.731***	-0.586**	-1.076***
0	(0.264)	(0.293)	(0.294)
Constant	7.264***	6.589***	6.592***
	(0.091)	(0.102)	(0.102)
Municipality FE	YES	YES	YES
Period FE	YES	YES	YES
Observations	2,088	1,994	1,998
R-squared	0.965	0.966	0.940

Table 4. Panel event-study regression for domestic, peninsular and local tourists.

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

			Monthly change		А	verage change	е
	Time	Domestic Tourism	Peninsular Tourism	Local Tourism	Domestic Tourism	Peninsular Tourism	Local Tourism
~	Lag 0	-26.43	-15.71	-36.49	-41.11	-39.01 -46.4	
otion	Lag 1	-52.52	-52.95	-55.11			-46.44
Erup	Lag2	-43.89	-44.62	-48.77			
Ι	Lag 3	-41.60	-42.76	-45.39			
ion	Lag 4	-52.47	-53.65	-54.97			
rupt	Lag 5	-57.64	-61.24	-58.68	-54.97	54 44	60.26
st-E	Lag 6	-57.93	-58.56	-61.51		-34.44	-00.20
Po_{c}	Lag 7	-51.85	-44.34	-65.90			

 Table 5. Percentage change in demand for each segment applying Halvorsen and Palmquist (1980)

 correction to the estimates in Table 4.

First, trips by peninsular tourists are typically booked further in advance than those by local tourists, which tend to be more spontaneous. Given the greater airfare costs peninsular tourists incur to arrive at the destination, they seem to be less likely to cancel their scheduled trips to the islands. Second, the lower decline in peninsular tourism could also be explained by a rise in what is generally known as *thanatourism*. The tourism literature has documented that curiosity about the outcomes of natural disasters and desire to help local people motivate some people to travel to affected areas, acting as a pull factor (e.g., Rittichainuwat, 2008).



Figure 7. Even study coefficient estimates and 95% confidence intervals for domestic tourism



Figure 8. Even study coefficient estimates and 95% confidence intervals for peninsular tourism



Figure 9. Even study coefficient estimates and 95% confidence intervals for local tourism

On the other hand, the comparatively greater drop in domestic flows after than during the eruption is potentially explained by the inflow of people from other islands in the Archipelago and Spain to battle the disaster. During the eruption, different media stayed at the island to report about the event. Several emergency professionals were also displaced there to collaborate in evacuation works.

Most of the event-study leads are non-significant, which rules out potential anticipation effects. The only significant one appears to be the seven-period lead, which is unlikely to be a serious concern. To inspect the parallel trend assumption closer, Figures A1-A3 in Appendix present graphical diagnostics for the time-evolution of the means of domestic, local and peninsular tourists (both the raw data and adjusted by linear trends, in logs) for municipalities in La Palma Island (treatment group) and the rest (control group). As demonstrated there, we do not reject the null hypothesis that pre-treatment trends are parallel. This suggests that demand in treated and non-treated municipalities was following similar trends prior to the eruption.

As previously explained, in light of the high correlation among the municipality controls (as shown in Table 3) and because of the potential biases of introducing endogenous time-varying covariates, our primary analysis only includes period and unit fixed effects. For the sake of robustness, we re-estimate the panel event study model considering: (i) the number of firms in the municipality, and (ii) the number of employed people, separately. The results of these additional regressions can be found in Appendix (Tables A1-A3) and are quite consistent with the main results.

6. CONCLUDING REMARKS

This paper analyses the effects of *Cumbre Vieja* volcanic eruption on the number of domestic tourists visiting La Palma Island. The work builds upon Leoni and Boto-Garcia (2022), by exploring the inflow dynamics of local (those living in other islands in the Archipelago) and peninsular (those coming from the rest of Spain) tourists following the eruption. We use a panel dataset based on mobile phone records at the municipal level, which allows us to conduct a more fine-grained analysis of the spatial-temporal inflows of visitors to all the islands in the Archipelago.

We adopt a difference-in-differences research design that uses the rest of islands as a control group, and present empirical evidence of a significant decrease in domestic tourism (both

among those coming from other Spanish regions and among local residents) following the event. Importantly, such drop persists throughout the months following the cessation of the eruption. On average, we estimate a 41-percentage point decrease in total domestic tourism during the eruption period (September 2021-December 2021). The effect is found to be stronger for local (-46 pp) than for peninsular (39 pp) tourists. Moreover, the decrease in arrivals is harsher in the post eruption period (January 22- April 2022), with a recorded drop of about 55 pp in total flows. Again, the drop is more pronounced for local (-60 pp) than for peninsular (-54 pp) tourists.

The work enriches the scant literature on the effect of volcano eruptions on visitors' flows, which are considered among the most detrimental natural disasters for tourism activities (Rosselló et al., 2020). This is particularly timely for island economies whose economy is highly dependent on the tourism sector (Seetanah, 2011). In the advent of a natural disaster, the documented drop in the number of tourists is the result of capital infrastructure destruction, mobility restrictions to affected areas and travellers' risk-aversion. Given the critical role that tourism plays in the economy of the Archipelago, it is essential that public authorities prioritize the recovery of tourism inflows.

For this purpose and aside from public investments in infrastructure and funding for the reconstruction of affected areas, policy makers and destination managers should work to alleviate risk concerns among potential visitors. As discussed in Yang et al., (2022) government efficiency plays an important role in moderating the negative effects on inbound tourist arrivals due to natural disasters. An efficient disaster management must be in possession of accurate information about affected areas in order to reduce tourists' concerns. At the same time, the volcano eruption could be used as a marketing tool for tourism recovery. Many people feel attracted by geothermal destinations, and volcano tourism is emerging as a form of sustainable tourism in which people value strong aesthetics and scenic values (Heggie, 2009). Visiting volcanic destinations is thus associated with adventure and discovering uncommon environments. Promoting dark tourism and tour itineraries throughout the areas where lava flowed could be a valuable mechanism to re-start and even increase tourism demand to La Palma Island. In this vein, social media emerges as a key channel for destination promotion after natural disasters (Ai et al., 2020), and public authorities should not disregard its importance as a way to publicly disseminate a sense of safety and to enhance visitors' willingness to travel to the island.

The study is not without limitations. The most important one concerns the temporal frame examined in our study, which focuses on the short-term effects of the eruption only. Future studies should expand our work by examining the middle and long-term dynamics of tourism flows recovery. Such analysis would provide additional insights about the resilience of the tourism industry, better quantifying the economic and social costs of such events in the long-term and facilitating a more comprehensive assessment of the benefits of disaster prevention and mitigation efforts.

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APPENDIX



Figure A1. Graphical diagnostics for parallel trends for log domestic tourists (raw data on the left; adjusted linear-trends model on the right)

Note: F test for H0: Linear trends are parallel: F(1,84)=0.02, P-value=0.978.





Note: F test for H0: Linear trends are parallel: F(1,87)=0.40, P-value=0.527.



Figure A3. Graphical diagnostics for parallel trends for log local tourists (raw data on the left; adjusted linear-trends model on the right)

Note: F test for H0: Linear trends are parallel: F(1,84)=1.69, P-value=0.197.

VariablesLog Domestic touristsLog peninsular touristsLog local touristsLead 7 0.261^{**} 0.306^{**} 0.256^{*} (0.122)(0.136)(0.137)Lead 6 0.114^{**} 0.090 0.146^{**} (0.056)(0.063)(0.064)Lead 5 0.035 -0.022 0.088 (0.087)(0.097)(0.097)Lead 4 -0.067 -0.034 -0.109 (0.104)(0.115)(0.116)Lead 3 -0.211^{*} -0.141 -0.202 (0.12)(0.127)(0.128)Lead 2 0.003 -0.078 0.067 (0.103)(0.115)(0.115)(0.115)Lag 0 -0.304^{***} -0.167 -0.450^{***} (0.125)(0.139)(0.140)Lag 1 0.726^{***} -0.730^{***} (0.142)(0.159)(0.160)Lag 2 0.054^{***} -0.634^{***} (0.161)(0.178)(0.179)Lag 3 -0.504^{***} -0.739^{***} (0.202)(0.225)(0.226)(0.225)(0.226)Lag 5 -0.840^{***} -0.739^{***} -0.72^{***} (0.225)(0.225)(0.226)(0.227)Lag 6 -0.836^{***} -0.923^{***} -0.863^{***} (0.247)(0.276)(0.277)Lag 7Lag 7 -0.715^{***} -0.571^{***} -1.064^{***} (0.262)(0.201)(0.202)Constant(0.76)(0.201)(0.202)Constant <th></th> <th>(1)</th> <th>(2)</th> <th>(3)</th>		(1)	(2)	(3)
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Lead 2 0.003 -0.078 0.067 (0.103) (0.115) (0.115) Lag 0 -0.304^{**} -0.167 -0.450^{***} (0.125) (0.139) (0.140) Lag 1 -0.726^{***} -0.730^{***} -0.781^{***} (0.142) (0.159) (0.160) Lag 2 -0.540^{***} -0.547^{***} -0.634^{***} (0.161) (0.178) (0.179) Lag 3 -0.504^{***} -0.518^{***} -0.571^{***} (0.181) (0.201) (0.202) Lag 4 -0.718^{***} -0.722^{***} (0.202) (0.225) (0.226) Lag 5 -0.840^{***} -0.923^{***} -0.72^{***} (0.202) (0.225) (0.226) Lag 6 -0.836^{***} -0.923^{***} -0.863^{***} (0.225) (0.250) (0.277) Lag 6 -0.836^{***} -0.923^{***} -0.924^{***} (0.247) (0.276) (0.277) Lag 7 -0.715^{***} -0.571^{**} -1.064^{***} (0.262) (0.291) (0.292) Ln firms 1.055^{***} 1.186^{***} 1.012^{***} (0.986) (1.139) (1.144) Municipality FEYESYESYESPeriod FEYESYESYESObservations 2.088 1.994 1.998 R-squared 0.966 0.967 0.941		(0.112)	(0.127)	(0.128)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Lead 2	0.003	-0.078	0.067
Lag 0 -0.304^{**} -0.167 -0.450^{***} (0.125)(0.139)(0.140)Lag 1 -0.726^{***} -0.730^{***} -0.781^{***} (0.142)(0.159)(0.160)Lag 2 -0.540^{***} -0.547^{***} -0.634^{***} (0.161)(0.178)(0.179)Lag 3 -0.504^{***} -0.518^{***} -0.571^{***} (0.181)(0.201)(0.202)Lag 4 -0.718^{***} -0.739^{***} -0.772^{***} (0.202)(0.225)(0.226)Lag 5 -0.840^{***} -0.923^{***} -0.863^{***} (0.225)(0.250)(0.252)Lag 6 -0.836^{***} -0.845^{***} -0.924^{***} (0.247)(0.276)(0.277)Lag 7 -0.715^{***} -1.064^{***} (0.262)(0.291)(0.292)Ln firms 1.055^{***} 1.186^{***} 1.012^{***} (0.176)(0.201)(0.202)Constant 1.385 -0.091 0.897 (0.986) (1.139) (1.144) Municipality FEYESYESPeriod FEYESYESYESYESYESObservations $2,088$ $1,994$ $1,998$ R-squared 0.966 0.967 0.941		(0.103)	(0.115)	(0.115)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Lag 0	-0.304**	-0.167	-0.450***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	•	(0.125)	(0.139)	(0.140)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Lag 1	-0.726***	-0.730***	-0.781***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	•	(0.142)	(0.159)	(0.160)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Lag 2	-0.540***	-0.547***	-0.634***
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	•	(0.161)	(0.178)	(0.179)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Lag 3	-0.504***	-0.518***	-0.571***
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	-	(0.181)	(0.201)	(0.202)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Lag 4	-0.718***	-0.739***	-0.772***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	•	(0.202)	(0.225)	(0.226)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Lag 5	-0.840***	-0.923***	-0.863***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.225)	(0.250)	(0.252)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Lag 6	-0.836***	-0.845***	-0.924***
Lag 7 -0.715*** -0.571** -1.064*** (0.262) (0.291) (0.292) Ln firms 1.055*** 1.186*** 1.012*** (0.176) (0.201) (0.202) Constant 1.385 -0.091 0.897 (0.986) (1.139) (1.144) Municipality FE YES YES YES Period FE YES YES YES Observations 2,088 1,994 1,998 R-squared 0.966 0.967 0.941		(0.247)	(0.276)	(0.277)
(0.262) (0.291) (0.292) Ln firms 1.055*** 1.186*** 1.012*** (0.176) (0.201) (0.202) Constant 1.385 -0.091 0.897 (0.986) (1.139) (1.144) Municipality FE YES YES Period FE YES YES Observations 2,088 1,994 R-squared 0.966 0.967 0.941	Lag 7	-0.715***	-0.571**	-1.064***
Ln firms 1.055*** 1.186*** 1.012*** (0.176) (0.201) (0.202) Constant 1.385 -0.091 0.897 (0.986) (1.139) (1.144) Municipality FE YES YES Period FE YES YES Observations 2,088 1,994 1,998 R-squared 0.966 0.967 0.941		(0.262)	(0.291)	(0.292)
(0.176) (0.201) (0.202) Constant 1.385 -0.091 0.897 (0.986) (1.139) (1.144) Municipality FE YES YES Period FE YES YES Observations 2,088 1,994 1,998 R-squared 0.966 0.967 0.941	Ln firms	1.055***	1.186***	1.012***
Constant 1.385 -0.091 0.897 (0.986) (1.139) (1.144) Municipality FE YES YES Period FE YES YES Observations 2,088 1,994 1,998 R-squared 0.966 0.967 0.941		(0.176)	(0.201)	(0.202)
(0.986) (1.139) (1.144) Municipality FE YES YES YES Period FE YES YES YES Observations 2,088 1,994 1,998 R-squared 0.966 0.967 0.941	Constant	1.385	-0.091	0.897
Municipality FEYESYESPeriod FEYESYESObservations2,0881,994R-squared0.9660.967		(0.986)	(1.139)	(1.144)
Period FE YES YES Observations 2,088 1,994 1,998 R-squared 0.966 0.967 0.941	Municipality FE	YES	YES	YES
Observations2,0881,9941,998R-squared0.9660.9670.941	Period FE	YES	YES	YES
R-squared 0.966 0.967 0.941	Observations	2,088	1,994	1,998
	R-squared	0.966	0.967	0.941

 Table A1. Panel event-study regression for domestic, peninsular and local tourists using number of firms (in logs) as a control.

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)
Variables	Log Domestic	Log peninsular	Log local
	tourists	tourists	tourists
Lead 7	0.244**	0.298**	0.253*
	(0.123)	(0.138)	(0.138)
Lead 6	0.108*	0.080	0.144**
	(0.057)	(0.064)	(0.064)
Lead 5	0.037	-0.020	0.090
	(0.088)	(0.098)	(0.098)
Lead 4	-0.057	-0.024	-0.100
	(0.104)	(0.116)	(0.116)
Lead 3	-0.201*	-0.123	-0.189
	(0.113)	(0.128)	(0.129)
Lead 2	0.016	-0.064	0.081
	(0.104)	(0.116)	(0.116)
Lag 0	-0.307**	-0.171	-0.456***
	(0.127)	(0.140)	(0.140)
Lag 1	-0.750***	-0.756***	-0.811***
	(0.143)	(0.160)	(0.161)
Lag 2	-0.588***	-0.600***	-0.686***
	(0.162)	(0.180)	(0.180)
Lag 3	-0.551***	-0.567***	-0.625***
	(0.183)	(0.202)	(0.203)
Lag 4	-0.757***	-0.775***	-0.820***
	(0.204)	(0.227)	(0.227)
Lag 5	-0.876***	-0.964***	-0.907***
	(0.227)	(0.252)	(0.253)
Lag 6	-0.885***	-0.898***	-0.982***
	(0.249)	(0.278)	(0.278)
Lag 7	-0.750***	-0.609**	-1.100***
	(0.264)	(0.293)	(0.294)
Ln Employed	0.003	0.008	-0.007
	(0.024)	(0.029)	(0.029)
Constant	7.239***	6.540***	6.646***
	(0.213)	(0.252)	(0.252)
Municipality FE	YES	YES	YES
Period FE	YES	YES	YES
Observations	2,064	1,970	1,974
R-squared	0.966	0.967	0.941

Table A2. Panel event-study regression for domestic, peninsular and local tourists using number of employed people (in logs) as a control.

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1