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CHAPTER 3

TOURISM ARRIVALS AND ROAD VICTIMS: EVIDENCE FROM MEDITERRANEAN REGIONS

1. Introduction

Despite the greater traffic congestion on roads, during peak season, most tourists in Mediterranean countries still choose to drive since that gives them greater flexibility in scheduling leisure or destination visiting. In addition, modern cars have become more comfortable, reliable, and safer with power steering, four-wheel drive, improved tires, air conditioning, cell phones, and advanced audio equipment. Yet, tourist driving is a risky activity. There are many uncertainties in tourist driving: the time taken on a tourist trip, the speed achieved on the trip, the chance of crashing, and the occurrence of a traffic accident, are all uncertain. A tourist in the role of driver will typically care about all of these possible outcomes. In addition, drivers tolerate various levels of risk and perception of risk has been shown to influence driving behavior [1,2,3].

Some features of a risk-loving driver include: drowsy driving (the dangerous combination of driving and sleepiness or fatigue), illegal parking, and driving under the influence of alcohol, narcotics or other impairments. If drivers in tourist destinations are *risk averse*, their utility of a certain outcome is greater than their utility of an expected value equal to the certain outcome. They will avoid the possibility of paying parking fines and avoid the hazard of motor vehicle collisions by adopting defensive-driving techniques. Risk-averse drivers' actions can keep travellers safe on the road more than those of risk-loving drivers.

When a tourist, as an economic agent, decides to drive to a tourist destination during high-season months, he takes into account the extra time it will take because of congestion on the roads at those times. Naturally, the slowing down of traffic is caused by risk-averse people on the road. Even the risk-loving driver becomes occasionally risk-averse on some occasions. However, a risk-averse driver generally does not take into account the effects of his driving on the congestion faced by others. This increase in the congestion he causes others is a negative externality. Adding up all these small externalities over thousands of personal vehicles totals a large aggregate externality. This translates to a large increase in paying attention to traffic by risk-averse drivers, which luckily, results in fewer accidents on the road.

Reviewing more recent literature about road accidents and tourism, we do see rare, but inspiring positive contributions of others' work. Road transport and tourism have been shown to be highly connected [4]. A rise in the number of tourists in many destinations and their increased mobility in host countries or regions have led to a growth in tourism-associated externalities. In one paper, the authors investigate different strategies in tourism policies designed to reduce the number of tourists using private motor vehicle

transport and to promote public, group or charter transport on the Balearic Islands [5]. Other authors estimated the impact of high ambient temperatures on the daily number of motor vehicle crashes in Catalonia, Spain (2000-2011) and, in particular, on crashes involving driver performance factors, namely, distractions, driver error, fatigue, and sleepiness [6]. Another paper explored the relationship between tourism and traffic congestion and hyper-congestion using a case study of Mallorca (Spain), one of the most important resort destinations in the Mediterranean [7].

In this paper, we seek to prove a causal relationship between tourism arrivals per surface and road victims per capita by exploiting data for tourism and traffic accidents with victimised individuals in 88 Mediterranean regions over the period 1995 to 2015. We utilise a causality test based on the generalised method of moments (GMM) and panel Granger causality tests.

2. Methodology

Our basic idea to which we will apply empirical testing, is that tourist arrivals co-vary with road victims directly because of heterogeneous unobservable factors, summed up as a combination of risk-averse (or loving) drivers. The expected results will try to determine whether tourism arrivals Granger-cause road victims or there is no evidence to suggest that tourism arrivals have an impact on killed or injured persons. The general theoretical assumption on which we will base our model is that all arrivals come on road vehicles. Although we know that that is not true, we will persist with this assumption for the sake of simplicity.

Since one of the main objectives of this study is to investigate the presence of a causal relationship, we explicitly address the direction of causation between road victims and tourist travellers using Granger causality [8] in a panel data setting, which is well-known for its strong intuitive appeal. We estimate Granger test equations using GMM methods. This methodology provides a very suitable tool to examine hypotheses regarding the strength, direction, determinants and consequences of tourist activity on victims of road traffic. The bivariate Granger causality test is a useful device to determine whether the lags of a variable, say, X_{it} , contribute to a better forecasting of Y_{it} when the lagged values of X_{it} are introduced into the regression of Y_{it} on the lagged values of Y_{it} and X_{it} . The same is for a trivariate Granger causality test. Thus, we estimate a time-stationary VAR model adapted to a panel context (as in [9]) in the form:

$$Y_{i,t} = \alpha_0 + \sum_{l=1}^m \beta_l Y_{i,t-l} + \sum_{l=1}^m \delta_l X_{i,t-l} + \sum_{l=1}^m \phi_l Z_{i,t-l} + \mu_i + u_{i,t} \quad (1)$$

Y_{it} , X_{it} and Z_{it} are the “rate of people killed (or injured) in road accidents per capita”, “tourists arrivals per square kilometer”, and “index of equivalent tourist population and residents”, respectively. In the final step, we explore whether the effect of tourists on road victims is significantly different from that of residents and tourists in order to discriminate the solitary impact of tourists. In the N regions (indexed by i) observed over T periods (indexed by t), l is the time lag.

We allow for region-specific effects μ_i . The disturbances $u_{i,t}$ are assumed to be independently distributed across regions with a zero mean. They may display heteroscedasticity across time and regions, however.

The best solution to deal with a dynamic panel problem is still a subject of debate in the econometric literature [10, 11]. It is known that the fixed effects estimates of this model are inconsistent for finite values of T , and it is consistent when T and N tend to infinity. Our current data have substantial a sample size in the cross-section dimension (88 regions), whereas the time dimension (21 years) is much smaller. However the generalised method of moments (GMM) estimator may produce consistent and asymptotically efficient estimates, especially when T is small. This paper adopts the Arellano-Bond [12] estimator that derives a GMM estimator for the parameters to be estimated on the right-hand side, using lagged levels of the dependent variables and differences of the exogenous variables. This estimator requires first-differencing to remove the fixed-effects in the equation. It also assumes that there is no second-order autocorrelation in the first-differenced idiosyncratic errors, which will be formally tested by Arellano-Bond test. The hypothesis that tourist arrivals Granger-cause traffic accidents can be tested by imposing the following restriction on the parameters of Equation 1. The null-hypotheses are: a) $H_0: \delta_l = 0$; b) $H_0: \varphi_l = 0$; c) $H_0: \delta_l + \varphi_l = 0$. In other words, based on the estimation results, a conclusion on causality will be reached by running Wald tests on the coefficients of the lagged X_{ts} and Z_{ts} to check whether they are alone and jointly statistically different from zero.

3. Data

Because there are minor gaps in some time series for selected regions, the missing data are imputed by using software applications to insert missing data [13]. The data set consists of balanced panel data, spanning the years 1995 to 2015. The variables used in this study and their descriptive statistics are shown in Table 1.

Table 1. Variables and descriptive statistics

VARIABLES	SOURCE	MEAN	SD	MIN	MAX
<i>kilcap</i>	Eurostat	11.26	6.46	0	44.43
<i>injc</i>	Eurostat	327.569	197.882	0	1305.373
<i>ars</i>	Eurostat	441.43	785.87	13.39	5028.75
<i>equp</i>	Eurostat	18359.22	20134.83	278.92	102433.1

Note: *kilcap* = rate of people killed in road accidents per 100,000 population, *injc* = rate of people injured in road accidents per 100,000 population, *ars* = tourist arrivals per square kilometer, *equp* = equivalent tourist population and residents calculated as: (number of residents x number of overnights) / 365.

The list of regions used in the analysis can be found in Table 2.

Table 2. List of regions analyzed

REGIONS, BASED ON LEVEL 2 OF THE NUTS CLASSIFICATION			
Galicia	Upper Normandy	Valle d'Aosta	North
"ES11"	"FR23"	"ITC2"	"PT11"
Asturias	Central France	Liguria	Algarve
"ES12"	"FR24"	"ITC3"	"PT15"
Cantabria	Lower Normandy	Lombardy	Central Portugal
"ES13"	"FR25"	"ITC4"	"PT16"
Basque Country	Burgundy	Abruzzo	Lisbon
"ES21"	"FR26"	"ITF1"	"PT17"

Navarre	Nord/Pas-de-Calais	Molise	Alentejo
"ES22"	"FR30"	"ITF2"	"PT18"
Rioja	Lorraine	Campania	Azores
"ES23"	"FR41"	"ITF3"	"PT20"
Aragon	Alsace	Apulia	Madeira
"ES24"	"FR42"	"ITF4"	"PT30"
Madrid	Franche-Comté	Basilicata	East Slovenia
"ES30"	"FR43"	"ITF5"	"SI03"
Castile and Leon	Loire Region	Calabria	West Slovenia
"ES41"	"FR51"	"ITF6"	"SI04"
Castile-La Mancha	Brittany	Sicily	Attica
"ES42"	"FR52"	"ITG1"	"EL30"
Extremadura	Poitou-Charentes	Sardinia	North Aegean
"ES43"	"FR53"	"ITG2"	"EL41"
Catalonia	Aquitaine	Autonomous Province of Bolzano"ITH1"	South Aegean
"ES51"	"FR61"		"EL42"
Valencia	Midi-Pyrénées	Autonomous Province of Trento"ITH2"	Crete
"ES52"	"FR62"		"EL43"
Balearic Islands	Limousin	Veneto	East Macedonia, Thrace
"ES53"	"FR63"	"ITH3"	"EL51"

Andalusia	Rhône-Alpes	Friuli-Venezia Giulia	Central Macedonia
"ES61"	"FR71"	"ITH4"	"EL52"
Murcia	Auvergne	Emilia-Romagna	West Macedonia
"ES62"	"FR72"	"ITH5"	"EL53"
Ceuta	Languedoc-Roussillon	Tuscany	Epirus
"ES63"	"FR81"	"ITI1"	"EL54"
Melilla	Provence-Alpes-Côte d'Azur	Umbria	Thessaly
"ES64"	"FR82"	"ITI2"	"EL61"
Canary Islands	Corsica	Marche	Ionian Islands
"ES70"	"FR83"	"ITI3"	"EL62"
Île-de-France	Adriatic Croatia	Lazio	Western Greece
"FR10"	"HR03"	"ITI4"	"EL63"
Champagne-Ardenne	Continental Croatia	Cyprus	Continental Greece
"FR21"	"HR04"	"CY00"	"EL64"
Picardie	Piedmont	Malta	Peloponnese
"FR22"	"ITC1"	"MT00"	"EL65"

Note: Source: Eurostat. NUTS - Nomenclature of territorial units for statistics.

4. Results

As Granger-causality tests require stationary data, all time series are tested for the presence of unit roots, applying a battery of now standard panel unit root tests (Maddala-Wu, Levin-Lin-Chu, Im-Pesaran-Shin and Hadri tests). The unit root test results show

that all encompassed variables in the analysis are stationary in levels for all regions. For reasons of space, the unit root tests are not addressed in this paper.

The GMM specifications include period-specific effects (as recommended in the literature). Lags of the dependent variable from at least one period earlier serve as GMM-style instruments. Since Granger-causality test results are sensitive to the choice of lag length in the time stationary VAR model given by Eq. (1), it is important to specify the lag structure appropriately. We follow Atukeren [14] in estimating Equation 6 with OLS and base the choice of the optimal lag length on the Schwarz Information Criterion (SIC). We find that the optimal lag length is 2.

In this section, the core results of Arellano-Bond dynamic panel estimations of a Granger-causality framework are presented in Table 3 and Table 4.

Tables 3 and 4 summarise the core results of estimations that include the logarithm level of *ars* alone and with *ars* and *equp* as controls. The *ars* level controls for the effect of arrivals per surface on road victims, which can be negative as well as positive. It is positive if tourist drivers, proxied by arrivals, shift the trajectory path of accidents away from less to more, translating more negative externalities in the form of road accident problems. The estimate for the effect of $\log(ars)$ on $\log(injcap)$ in one-step GMM is positive, which is statistically significant at the ten percent significance level. Otherwise, the direction of that coefficient, which is insignificant in all other estimations, would imply that an increase in concurrent tourism arrivals per surface leads to a decrease in the rate of killed or injured persons per 100,000 population. The AB test shows the test results for the presence of autocorrelation in the error terms. The p-values indicate that the null hypothesis of no autocorrelation cannot be rejected for all samples when the model includes two lags for the right-hand side variables.

Although the results are not absolutely robust, the following picture emerges from the bivariate Granger-causality test by one-step GMM. The log coefficients for long-term tourism arrivals are significantly negative, while the short-term coefficients (one-year lag) are insignificant. The second lag period's arrival does have a significant effect on the current period's rate of injured for our samples, where a negative inter-temporal effect is statistically significant at the ten percent level. Focusing solely on the Wald test results, we find clear evidence that tourism arrival intensity has a negative impact on injured persons, and that arrivals Granger-cause the rate of injured in a negative way as we suggested in introduction. Thus, we find significant evidence for that reasoning which lead us to conclude that risk-averse driving processed by tourist arrivals lessens the number of injured victims in the environment. At the tri-variate level, this finding also holds true: *equip* Granger-causes those injured in traffic accidents. This emphasises the impact of tourists and residents, taken together, on the rate of injured persons. Yet it is impossible to distinguish whether it is the solitary impact of *ars* or joint impact with *equip* in tri-variate Granger causality tests. When considering those killed on the road as a dependent variable, however, we see that this evidence is not conclusive, due to insignificant lagged control variables. Taking all into consideration, we are unable to find a uni-directional relationship running from *ars* or *equip* to *kilcap*.

Table 3. Do tourist arrivals Granger-cause the rate of road traffic fatalities?

	Bi-variate Granger causality tests among kilcap & ars		Tri-variate Granger causality tests among kilcap & ars, equ	
kilcap	Arellano-Bond	Arellano-Bond	Arellano-Bond	Arellano-Bond
	one-step GMM	two-step GMM	one-step GMM	two-step GMM
lag(log(<i>kilcap</i>),1)	0.417 (0.136)**	0.422 (0.137)**	0.407 (0.136)**	0.407 (0.136)**
lag(log(<i>kilcap</i>),2)	0.108 (0.063)	0.109 (0.065)	0.090 (0.068)	0.094 (0.069)
log(<i>ars</i>)	-0.338 (0.463)	-0.248 (0.472)	0.494 (0.589)	0.235 (0.664)
lag(log(<i>ars</i>),1)	0.248 (0.353)	0.337 (0.333)	-0.361 (0.440)	-0.236 (0.502)
lag(log(<i>ars</i>),2)	0.077 (0.133)	-0.093 (0.218)	0.425 (0.275)	0.421 (0.338)
log(<i>equip</i>)			-0.785 (0.502)	-0.670 (0.528)
lag(log(<i>equip</i>),1)			0.715 (0.475)	0.759 (0.481)
lag(log(<i>equip</i>),2)			-0.471 (0.278)	-0.516 (0.317)
Wald Test			0.000	0.000
<i>ars</i>	0.000	0.006		
Wald Test			0.000	0.000
<i>equip</i>				
Wald Test <i>ars</i> & <i>equip</i>			0.000	0.011
AB test (p-level)	0.027	0.981	0.024	0.889

Note: Standard errors are in parentheses. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively. Num.obs. (used) =1848 (1584). Estimates for

constant terms are not shown. Wald-test = p-value. AB test = Arellano-Bond test for AR (2) in first differences.

Table 4. Does tourist arrivals Granger-cause the rate of those injured in road traffic?

	Bi-variate Granger causality tests among injcap & ars		Tri-variate Granger causality tests among injcap & ars, equ	
	Arellano-Bond one-step GMM	Arellano-Bond two-step GMM	Arellano-Bond one-step GMM	Arellano-Bond two-step GMM
kilcap				
lag(log(<i>injcap</i>),1)	0.754 (0.062) ^{***}	0.752 (0.062) ^{***}	0.753 (0.062) ^{***}	0.753 (0.062) ^{***}
lag(log(<i>injcap</i>),2)	0.042 (0.056)	0.043 (0.056)	0.041 (0.055)	0.040 (0.055)
log(<i>ars</i>)	-0.102 (0.080)	-0.070 (0.130)	0.214 (0.108) [*]	0.220 (0.151)
lag(log(<i>ars</i>),1)	0.042 (0.077)	-0.040 (0.135)	-0.109 (0.077)	-0.164 (0.142)
lag(log(<i>ars</i>),2)	-0.143 (0.062) [*]	-0.173 (0.105)	-0.071 (0.065)	-0.077 (0.120)
log(<i>equip</i>)			-0.273 (0.096) ^{**}	-0.235 (0.122)
lag(log(<i>equip</i>),1)			0.173 (0.085) [*]	0.171 (0.137)
lag(log(<i>equip</i>),2)			-0.094 (0.054)	-0.056 (0.117)
Wald Test			0.039	0.052
<i>ars & equip</i>				
Wald Test			0.023	0.017
<i>ars</i>	0.000	0.000		

Wald Test			0.003	0.029
<i>equip</i>				
AB test (p-level)	0.215	0.188	0.214	0.885

Note: Ibid

5. Summary

This paper applies the method of Granger-causality testing to a panel of 88 Mediterranean regions over the period 1995-2015 to investigate the relationship between variations in tourist arrivals on road traffic accident victims, both injuries and deaths. All data is transformed into annual average growth rates, and the estimators chosen are Arellano-Bond type GMM estimators. It finds limited evidence that tourism arrivals have a reductive effect on rate of injured persons. The core results show that an increase in the log number of tourism arrivals is estimated to reduce the rate of injured, whereas tourism arrivals Granger-cause the rate of injured. With regard to an index of equivalent population and tourist arrivals, things look quite different. For instance, we do not see a negative causal relationship running from the whole population (tourist and residents) to the rate of injured or a one-directional relationship between these two variables (but not solely tourists). Our failure to clearly distinguish the source of casual impact on the rate of killed persons may speak of a certain futility of this study. Further investigation is required to examine the relationships of these variables in the channel more vigorously, which remains an important and challenging topic for future research.

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