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Terrorism and Wine Tourism: the case of Museum Attendance[*]

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Abstract

In this paper, we use attendance data from *La Cité du Vin*, a wine museum in the city of Bordeaux, to assess the impact of the recent wave of terror that hit France on wine tourism. We use recent count regression estimation techniques suited for time series data to build a prediction model of the demand for attendance at this museum. We conclude that the institution lost about 5,000 visitors over 426 days, during which 14 successive terrorist attacks took place (3% of the sample period). This corresponds to almost 1% of the total number of visitors of the sample period. (JEL Classifications: L83, Z30)

Keywords: wine tourism, tourism economics, museum attendance, terrorism

I. Introduction and Background

Following the dramatic mass shooting of January 2015, France experienced an unprecedented wave of terror with no fewer than 26 terrorist attacks[1] over its territory (targeting the offices of the *Charlie Hebdo* journal). French tourism suffered a severe contemporaneous decrease in the number of foreign visitorsaround 1.5 million tourists in 2016 compared with 2015 (CRT, 2016). Richardson et al. (2005) show that the number of tourists declines immediately after every terrorist attack in the country, with some positive and negative interregional effects. Terrorism has also more permanent effects (Becker and Rubinstein, 2008; Camacho, 2008). Frey et al. (2007) show that it takes between 2 and 21months to recover from a terrorist attack. The question that we raise in this article is as follows: what is the effect of the recent wave of terror in France on wine tourism? We use an original dataset on the number of visitors to *La Cité du Vin*, a museum in Bordeaux dedicated to the universe of wine, to analyze the evolution of the demand for attendance at this museum before, during and after the wave of terror.

Studies dealing with the determinants of attendance of wine museums are scarce. Research has focused on the effect of price on demand for the arts (Seaman, 2006) and for sports (Borland and MacDonald, 2003). *La Cité du Vin* has not changed its admission price since opening, hampering our ability to estimate price elasticity in demand and formulate an optimal pricing strategy. Skinner et al. (2009), who study museum attendance at an aggregate level, do not use price variables. As the museum's admission

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[1] https://en.wikipedia.org/wiki/List_of_terrorist_incidents_in_France#21st_century

price is fixed, the current study focuses instead on the impact of various events on the revenue of La *Cité du Vin*.

The literature on demand for attendance in the cultural field suggests several potential non-price determinants. For the motion picture industry, Einav (2007) sheds light on the role of seasonality and shows that films earn more on public and school holidays than during non-holiday periods. Weather is also included in some models of movie demand (Dahl and DellaVigna, 2009; Moretti, 2011; De Roos and McKenzie, 2014). Skinner et al. (2009) show that art museum attendance varies counter-cyclically with the business cycle. The demand for attendance at sporting contests allows to address the impact of new stadiums and arenas on season attendance. A honeymoon effect that lasts between 4 and 8 years (persistence of a positive effect on attendance) is detected by Zygmont and Leadley (2005) in a study of Major League Baseball from 1970 to 2000, by Leadley and Zygmont (2005) in research on the National Basketball Association from 1971 to 2000 and by Leadley and Zygmont (2006) in a study of the National Football League from 1994 to 2003, during which 21 new arenas opened.

Recent research on tourism demand suggests that using certain Internet search indexes relating to a destination improves the accuracy of time series models in forecasting the demand for hotel rooms (Pan et al., 2012) and the number of visitors (see Xi, et al., (2017) for Beijing; Önder and Gunter (2016) for Vienna). Bangwayo-Skeete and Skeete (2015) use a composite search index, “hotels and flights,” to forecast tourism in the Caribbean. Choi and Varian (2012) show that *Google Trends* (GT) data can be used to forecast tourist arrivals in Hong Kong, and Siliverstovs and Wochner (2018) show that these data are also accurate predictors for Switzerland. Addressing individual attractions, Volchek et al. (2018) find a high correlation between *Google Search* queries concerning the most popular London museums and actual visits. Last, *Baidu Analytics* is used by Huang et al. (2017) to forecast flows of visitors at the Forbidden Palace in Beijing.

The negative effect of terrorism on tourism demand is well documented in the literature: sharp reduction in tourist arrivals and expenditure in the incident regions (Sönmez, Backman, and Allen, 1994), significant decline in the numbers of visitors, followed by a very slow process of recovery (Seddighi, Nuttall and Theocharous, 2001). Bac, Bugnar and Mester (2015) find a time lag before a terrorist attack affects negatively the local tourism market. As most tourists are risk averse, they tend to change their tourist package preferences (Walters, Wallin, and Hartley, 2018) and to cancel or postpone their travel plans or travel to safer destinations in such situations (Bonham, Edmonds and Mak, 2006; Reisenger and Mavondo, 2005). Recently, empirical studies have shown that some destinations have benefited from certain terror events (Araña and León, 2008) because tourists tend to replace risky destinations with safer ones when there is a threat of terrorism (Sönmez, 1998). A substitution effect between different forms of tourism within the destinations at which the attacks take place is also likely. Internet search trends are also used by researchers to measure public attentiveness and issue salience, including in the case of terrorism (Mellon, 2013, 2014). Searches for “terrorism” might be a good proxy for this concern (Ripberger, 2011). However, Mellon (2013) finds that the name of a well identified terrorist group is not a good predictor of the salience of terrorism, and recommends dealing with language differences.

II. Data

To estimate the causal impact of terrorism on wine tourism, we collected museum attendance data at *La Cité du Vin*,[2] a wine museum in Bordeaux, France that first opened in June 2016. We use daily information on the number of visitors from the museum’s opening to December 31, 2017 (see Figure 1)

[2] See http://www.laciteduvin.com/en/explore-la-cite-du-vin/la-cite-du-vin-world-cultures

to estimate a demand equation for the museum. Such high-frequency data will allow us to assess the impact of the aforementioned terrorist attacks using distributed-lag time series models.

[Insert Figure 1 about here]

The number of visitors per day exhibits strong intra-weekly variations with pronounced weekend peaks. A correlogram[3] suggests an autoregressive model with seven lags (AR(7)). Unsurprisingly, the summer period seems to be busier than the rest of the year, although more data would be needed to confirm this seasonal phenomenon. We also include in our specifications a set of dummies to control for potential differences in attendance over the week, as well as a monthly time trend and a general time trend. The monthly time trend allows us to control for some degree of variation in the number of visitors over the month. Households typically have more money at the beginning of the month. However, visiting a museum is a luxury like most cultural goods and services. For this reason, the decision to visit *La Cité du Vin* may, for some households, can occur only later in the month, once normal goods are consumed. The general time trend is used to check whether the museum has experienced a honeymoon effect since its opening. We use the average daily temperature and a dummy variable that equals 1 if the day in question was rainy and 0 otherwise. We use specific temporal dummies to capture the effect of the presence of cruise ships in the city, as suggested by Gordin and Matetskaya (2012). On July 2, 2017, France inaugurated a new high-speed rail line linking the capital city to the city of Bordeaux. This rail line cuts the travel time from Paris to Bordeaux by more than an hour, from 3 hours and 14 minutes to only 2 hour and 4 minutes. We use this exogenous shock as a control variable in our model to assess the impact of this major infrastructural development on the demand for attendance at *La Cité du Vin* (0 before July 2nd, 2017, 1 after that date). *Google Trends* (GT) data offer insight into the intensity with which people search for information on the museum and whether Google searches translate into future visits to the museum.[4] We use the same search engine to proxy the intensity of people's concern about terrorist attacks. We searched for the keyword "terrorism" in both French and English, as recommended by Mellon (2013). These web analytics, which vary from 0 to 100, are integrated in our model with a series of lags (1 week and 2 week-lag). As an alternative approach, we use a set of 15 time dummies in our model to identify the two-week period following each attack. The French population experienced no fewer than 14 days of terror over the period investigated, i.e., 3.3% of the time.

We control for the general attractiveness of the city of Bordeaux using the number of French and foreign passengers arriving at Bordeaux airport (monthly indicator provided by *Bordeaux Métropole* Tourism Barometer).

Table 1 presents descriptive statistics for the dependent and the independent variables. We have full information for 426 days of attendance. The average number of visitors is around 138 per hour. Temporary exhibitions are quite frequent at *La Cité du Vin* (accounting for 46% of the sample period). School holidays and bank holidays amount to 38% of the sample period. Cruise ships dock frequently on Bordeaux (18% of the time). Around 550,000 air passengers travel to Bordeaux every month. More foreign passengers than French passengers arrive at Bordeaux airport.

[Insert Table 1 about here]

[3] Available from the authors upon request.

[4] We use simply the name of the museum, "*La Cité du Vin*" as a keyword in GT, which has a category for this museum.

III. Results

We use two estimators to identify the main determinants of the number of *La Cité du Vin* visitors per hour.[5] First, we use a negative binomial regression model with a robust covariance matrix estimator, as suggested by Cameron and Trivedi (2005), coupled with an AR(7) as indicated above. Indeed, unless count data are equi-dispersed, the usual Poisson maximum likelihood estimator standard errors will be wrong. Lags are used in this framework to deal with the presence of strong autocorrelation in the residuals. We also run a Poisson regression allowing for autocorrelation and over- dispersion (Schwartz et al., 1996) using the *arpois* user-written command in Stata. Although *arpois* offers a clear advantage over the usual negative binomial estimator in dealing with the time series dimension of our data, it does not compute robust standard errors. To overcome this limitation, and because the standard errors are not homoscedastic in our case, we bootstrap our estimates 500 times to obtain consistent standard deviations.

Table 2 displays four regression models. Regressions (1) and (3) contain the coefficients obtained using the negative binomial estimator with seven auto-regressive lagged terms (Neg. Bin. – AR hereafter) while regressions (2) and (4) show the results using the alternative Poisson approach (Poisson – AR hereafter). In regressions (1) and (2), we use GT to proxy the intensity with which people worry about terrorism both in English (for English-speaking visitors) and in French (for French-speaking visitors). In regressions (3) and (4), we use fifteen time dummies to check whether the attendance at *La Cité du Vin* varied significantly over the first two weeks following an attack. These various coefficients are reported in Table 3.

[Insert Table 2 about here]

The results are stable across the specifications and do not vary much with the estimator used. As anticipated, we observe strong positive AR(1) and AR(7) effects and a mild negative AR(2) effect. School and bank holiday coefficients have the expected positive sign (+4.31 and +46.8 visitors per hour respectively)[6]. Attendance figures are also significantly higher over the weekend, especially on Saturdays (+35.31 visitors per hour), and significantly lower on Mondays (-32.1 visitors per hour). Similar attendance scores for Sundays, which corresponds to the reference category, and for Tuesdays, Wednesdays and Fridays. Attendance is lower in warmer weather (-1.49 visitor per hour per degree Celsius) whereas rainy days encourage people to visit the museum (+15.9 visitors per hour). Attendance is also slightly lower during spring than in other seasons. We do not detect any significant attendance patterns over the month. However, the general time trend coefficient is negative and significant suggesting a limited but real honeymoon effect. In other words, attendance has decreased steadily over time since the museum opened. The marginal effect is around -0.72 visitors per day or 264 visitors per year. The new high-speed rail line between Paris and Bordeaux does not seem to affect the demand for attendance at *La Cité du Vin.* This suggests that tourism flow between Paris and Bordeaux has evolved proportionately since the new line opened. Nor does the presence of cruise ships in Bordeaux seem to significantly affect the number of visitors to the museum. The same is true of the number of French passengers commuting via Bordeaux airport. In contrast, the demand for attendance is positively affected by the number of foreign passengers (0.13 additional visitors per hour for 1,000 additional foreign passengers). Temporary exhibitions are a good way to attract a substantial number of additional visitors (+27.2 visitors per hour). Last, the intensity of Google searches associated with *La Cité du Vin*

[5] As the number of the museum's daily opening hours varies from 8 to 10.5, we regress the number of visitors per hour every day and discard days on which the museum was closed.
[6] Marginal effects were computed using model (3).

conducted one week before the visit (+2.15 visitors per hour per additional GT percentage point) has a positive effect on attendance. This suggests that GT is a valuable tool that should be used in the future to improve our predictions.

[Insert Table 3 about here]

Model (4) suggests that a given terrorist attack had a negative impact on the number of visitors to *La Cité du Vin* at four days and thirteen days after the attack (-25.73 and 13.73 visitors per hour respectively). This amounts to a loss of 365.6 visitors after each terrorist attack, representing an overall cost of 5,119 visitors for the 14 successive terrorist events over the sample period. The results obtained using GT indices for the keyword "terrorism" in French and in English suggest that one percentage point of additional concern/interest in the wave of terror had varied effects on the demand for attendance at the museum. Foreign visitors concerned about the attack seem to have visited La *Cité du Vin* in greater numbers one week after the attack and in smaller numbers three weeks after the attack. The positive effect is probably due to the decision made by foreign visitors already present in Europe to visit Bordeaux to escape the areas directly affected by the attack (mostly the Paris urban area). The negative effect three weeks after the attack probably reflects the decision made by a significant number of cautious visitors to cancel their trips to France. We observe opposite effects for the keyword "terrorisme" in French. A significant proportion of local visitors probably decided to avoid visiting public spaces immediately after the attack and thus postponed their visits by about two weeks. Note that the coefficients of GT— "terrorisme" at *t-1* and *t-3* are of equal magnitude.

Discussion and Conclusion

In this paper, we analyze the determinants of the demand for attendance at a wine museum in Bordeaux, *La Cité du Vin,* to examine the effect on wine tourism of France's recent wave of terror. Using several econometric techniques, we conclude that the museum lost about 5,000 visitors over 426 days, during which fourteen successive terrorist attacks occurred (3% of the sample period). This corresponds to almost 1% of the total number of visitors during the sample period.

We plan to extend the analysis to other tourism statistics in the future to confirm the results obtained in this paper. In particular, it would be interesting to apply the same methodology to the number of hotel nights in some popular wine tourism destinations in France, especially in countries hit by a similar wave of terror. Regarding *La Cité du Vin*, more observations would be needed to better characterize the seasonal pattern of the demand for attendance at this museum.

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Figure 1: Number of visitors per day at *La Cité du Vin,*
June 1, 2016-December 31, 2017

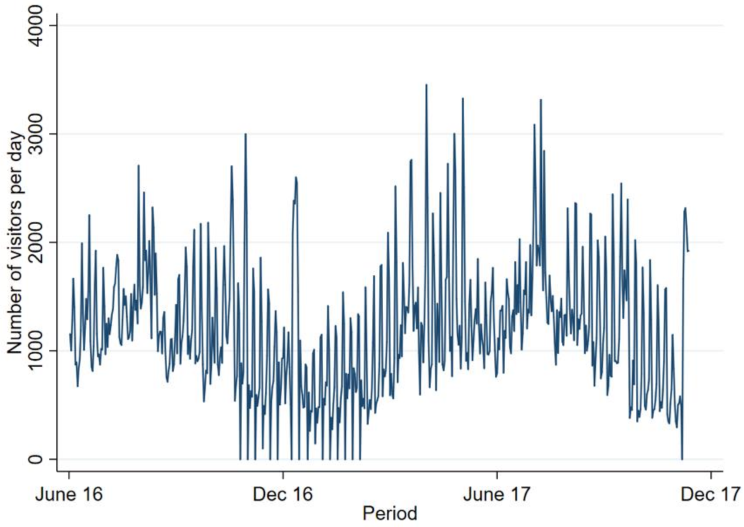

Table 1: Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Visitors per hour	426	138.46	57.055	37	363
Temporary exhibition	426	.46	.5	0	1
Temperature	426	16.75	5.87	0	29.1
Rainy day (0/1)	426	.38	.48	0	1
School holiday	426	.35	.48	0	1
Bank holiday	426	.03	.17	0	1
High speed train from Paris (2 hours)	426	.41	.49	0	1
Presence of a cruise ship in Bordeaux	426	.18	.38	0	1
Bordeaux airport: French passengers	426	257,062	22,133	218,804	300,977
Bordeaux airport: inter. Passengers	426	294,649	73,271	138,512	414,058
Google Trends					
« La Cité du Vin »	426	13.315	2.879	8	25
« Terrorism »	426	24.559	9.887	12	67
« Terrorisme »	426	29.423	15.202	14	89

Table 2: The main determinants of the demand for attendance at *La Cité du Vin* museum

	Negative binomial	Poisson AR	Negative binomial	Poisson AR
	Google Trends		*Time dummies*	
Log of (Visitors per hour) in *t-1*	0.402***	0.340***	0.426***	0.375***
	(0.047)	(0.068)	(0.047)	(0.068)
Log of (Visitors per hour) in *t-2*	-0.113**	-0.062	-0.104*	-0.043
	(0.055)	(0.059)	(0.055)	(0.060)
Log of (Visitors per hour) in *t-3*	-0.020	-0.104*	0.003	-0.062
	(0.049)	(0.059)	(0.047)	(0.059)
Log of (Visitors per hour) in *t-4*	-0.038	-0.044	-0.019	-0.016
	(0.044)	(0.056)	(0.045)	(0.056)
Log of (Visitors per hour) in *t-5*	-0.017	-0.037	-0.005	0.012
	(0.046)	(0.057)	(0.047)	(0.054)
Log of (Visitors per hour) in *t-6*	0.089*	0.038	0.095*	0.061
	(0.051)	(0.058)	(0.050)	(0.053)
Log of (Visitors per hour) in *t-7*	0.182***	0.215***	0.182***	0.235***
	(0.047)	(0.055)	(0.047)	(0.054)
Time variables :				
Day of the month	0.000	0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.001)	(0.002)
Overall time trend	-0.000**	-0.001*	-0.001***	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
School holidays in France	0.086**	0.119**	0.031	0.079**
	(0.036)	(0.047)	(0.030)	(0.039)
Bank holidays in France	0.343***	0.325***	0.338***	0.323***
	(0.061)	(0.086)	(0.067)	(0.083)
Monday	-0.235***	-0.324***	-0.232***	-0.312***
	(0.049)	(0.053)	(0.049)	(0.052)
Tuesday	-0.070	-0.287***	-0.075	-0.279***
	(0.049)	(0.047)	(0.049)	(0.044)
Wednesday	-0.070	-0.216***	-0.080*	-0.220***
	(0.045)	(0.050)	(0.046)	(0.049)
Friday	-0.092**	-0.074	-0.087**	-0.081*
	(0.044)	(0.048)	(0.044)	(0.048)
Saturday	0.246***	0.262***	0.255***	0.259***
	(0.046)	(0.047)	(0.046)	(0.047)
Season: (ref. cat. is Summer)				
Spring	-0.167**	-0.190**	-0.069	-0.178**
	(0.069)	(0.080)	(0.059)	(0.083)
Fall	-0.027	-0.014	-0.004	0.002
	(0.041)	(0.060)	(0.038)	(0.052)
Winter	-0.071	-0.118	-0.000	-0.112
	(0.093)	(0.119)	(0.094)	(0.126)
Temporary exhibition	0.257***	0.368***	0.197***	0.360***
	(0.050)	(0.050)	(0.049)	(0.054)
Temperature in degrees Celsius	-0.011***	-0.014**	-0.011***	-0.013**
	(0.004)	(0.006)	(0.004)	(0.006)
Rainy day (No=0/Yes=1)	0.125***	0.162***	0.115***	0.149***
	(0.028)	(0.035)	(0.025)	(0.033)

High speed train from Paris	-0.038	-0.036	0.021	-0.067
	(0.092)	(0.114)	(0.067)	(0.102)
Presence of a cruise ship	0.005	0.022	0.004	0.021
	(0.032)	(0.040)	(0.030)	(0.040)
Airport: French passengers	0.000	0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Airport: inter. passengers	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Google Trends « La Cité du Vin »				
One-week lag	0.000	0.012*	0.004	0.015**
	(0.005)	(0.006)	(0.004)	(0.006)
Two-week lag	-0.005	0.004	-0.005	-0.001
	(0.005)	(0.006)	(0.004)	(0.005)
Constant	2.178***	4.106***	1.824***	4.333***
	(0.472)	(0.374)	(0.451)	(0.303)
Observations	424	410	440	426
R-squared		0.628		0.625

Robust standard errors in parentheses for models (1) and (3). Bootstrapped standard errors with 500 replications for models (2) and (4); *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Impact of the "Terrorism" variables

	Neg. Binomial AR	Poisson AR		Neg. Binomial AR	Poisson AR
	Google Trends			*Time dummies*	
« Terrorism »			Terrorist attack		
One-week lag	0.004**	0.005**	on that day	0.043	0.048
	(0.002)	(0.002)		(0.066)	(0.104)
Two-week lag	-0.001	-0.002	1 day before	-0.038	-0.023
	(0.002)	(0.003)		(0.055)	(0.083)
Three-week lag	-0.004**	-0.006**	2 days before	-0.067	-0.073
	(0.002)	(0.002)		(0.049)	(0.073)
Four-week lag	0.002	0.002	3 days before	-0.071	-0.106
	(0.001)	(0.002)		(0.068)	(0.075)
« Terrorisme »			4 days before	-0.101*	-0.186**
One-week lag	-0.003**	-0.004**		(0.056)	(0.079)
	(0.001)	(0.002)	5 days before	0.040	-0.033
Two-week lag	0.000	-0.000		(0.050)	(0.068)
	(0.002)	(0.002)	6 days before	0.065	0.027
Three-week lag	0.003**	0.004**		(0.052)	(0.059)
	(0.002)	(0.002)	7 days before	0.011	0.082
Four-week lag	0.000	0.001		(0.049)	(0.087)
	(0.001)	(0.002)	8 days before	0.082*	0.099
				(0.049)	(0.072)
			9 days before	0.123	0.144
				(0.075)	(0.087)
			10 days before	0.061	0.081
				(0.088)	(0.111)
			11 days before	-0.034	-0.076
				(0.052)	(0.071)
			12 days before	-0.066	-0.071
				(0.047)	(0.067)
			13 days before	-0.089*	-0.099*
				(0.053)	(0.060)
			14 days before	0.081	0.035
				(0.054)	(0.093)

Marginal effects have been generated using the margins command in Stata and are available from the authors upon request.