Is there a Causal Relationship between Oil Prices and Tourist Arrivals?

September 19, 2018

Abstract

This application note investigates the causal relationship between oil price and tourist arrivals to further explain the impact of oil price volatility on tourism related economic activities. The analysis itself considers the time domain, frequency domain and information theory domain perspectives. Data relating to the US and nine European countries are exploited in this paper with causality tests which include time domain, frequency domain, and Convergent Cross Mapping (CCM). The CCM approach is nonparametric and therefore not restricted by assumptions. We contribute to existing research through the successful and introductory application of an advanced method, and via the uncovering of significant causal links from oil prices to tourist arrivals.

Keywords: Oil price; tourist arrivals; causality; convergent cross mapping; granger causality.

1 Introduction

In the recent past, it was oil prices hikes that influenced investigations into the relationship between tourism and oil price fluctuations [1]. However, today it is falling oil prices that continue to necessitate further investigations, and given the tourism industry's energy-intensive nature [1,2] it is not surprising that the relationship between oil prices and tourist arrivals remains a crucial research topic. This relationship has drawn significant attention [2–5] as the accurate detection of causality between oil prices and tourist arrivals can help the tourism planning process and aid in improving the quality of tourist arrival forecasts and related managerial decisions [35].

Previous research indicates negative effects between oil price and tourism [3,5], which is identified with overwhelming evidences from factors like inflation, CPI, oil production, tourism income, and industrial production indices. A critical review of the studies on tourism and oil can be found in [6] and therefore these are not reproduced here. With regard to the more recent causality testing applications relating to tourist arrivals from 2012 onwards, Granger causality test under a vector autoregression framework [7–12,14–22] or with an error correction model [23–33] continue to remain the mainstream methods for assessing causality between tourist arrivals and influential variables, the literature has expanded its horizon to a global scale that cover a variety of countries/regions, i.e. Malaysia [24,29,30], Jamaica [25], Italy [8], Spain [26], Singapore [27], Cyprus [28], Lebanon [9], OECD countries [10], EU [11,14,15,34], Taiwan [12], US [14], Turkey [33], China [17,21], and Australia [22] (to name a few).

The main aim of this application note is to further evaluate this oil-tourism relationship and efficiently investigate the existence of causal links by conducting a data driven research with an advanced non-parametric method known as Convergent Cross Mapping (CCM) [36]. Instead of building a complex model by incorporating many possible influential variables based on regression modelling which is restricted by a number of assumptions, this paper adopts CCM which is popular for its significant sensitivity at detecting causal links within complex systems whilst not being restricted by assumptions pertaining to linearity or nonlinearity. It only requires two key variables for conducting analyses with proven robust and sufficient performance even with the existence of common determinants.

Moreover, another motivation of conducting this research is to reflect the inherent efficiency and power of CCM in relation to empirical tests so as to further promote its use in future. Accordingly, we seek to find significant evidences of oil-tourism causal relationships on a global scale by involving only the two key variables - oil price and tourist arrivals alone as an alternative data driven approach that empirical methods fail to do so. It is acknowledged that the existence of a variety of determinants in oil-tourism literature and the establishments of model based analyses, and this paper is not providing suggestion of replacing any statistical test, but an alternative, data-driven path that can still achieve better understanding of their relationship without the complex model.

The results from CCM are compared with two empirical causality methods which fall under the time domain and frequency domain criteria. To the best of our knowledge, this application note marks the introductory and successful adoption of CCM for identifying causality between oil price and tourist arrivals. Accordingly this research presents three contributions to scientific literature on causality between oil and tourism. Firstly, our research focuses on a data driven investigation of causal effects across both US and nine European countries via the introductory application of CCM. Secondly, we consider monthly data in our analysis and this is important as such data is seldom used in the analysis of causal relationships between tourism demand and its influencing factors [14, 37]. Thirdly, our findings enable us to prove that this advanced and assumption free CCM causality test is a robust, solid and efficient method that can produce reliable evidences by using only two key variables. As such, it is possible to introduce CCM as a method with great potential for other causal analyses in tourism studies and more importantly in a broader range of subjects.

2 Methodology of Causality Tests

2.1 Convergent Cross Mapping (CCM)

CCM was introduced in [36] with the aim of detecting the causation among time series and providing a better understanding of the dynamical systems that have not been covered by other well established methods like Granger causality. CCM has proven to be an advanced non-parametric technique for distinguishing causation in a dynamic system that contains complex interactions covering a broad range of subjects [39–41]. CCM is briefly introduced below by mainly following [36].

Assume there are two variables X_i and Y_i, for which X_i has a causal effect on Y_i. CCM test will test the causation by evaluating whether the historical record of Y_i can be used to obtain reliable estimates of X_i. Given a library set of n points (not necessarily the total number of observations N of two variables) and here set $i = 1, 2, \cdots, n$, the lagged coordinates are adopted to generate an E-dimensional embedding state space [42,43], in which the points are the library vector X_i and prediction vector Y_i

$$X_i \quad : \quad \{x_i, x_{i-1}, x_{i-2}, \cdots, x_{i-(E-1)}\}, \tag{1}$$
$$Y_i \quad : \quad \{y_i, y_{i-1}, y_{i-2}, \cdots, y_{i-(E-1)}\}. \tag{2}$$

The $E+1$ neighbors of Y_i from the library set X_i will be selected, which actually form the smallest simplex that contains Y_i as an interior point. Accordingly, the forecast is then conducted by this process, which is the nearest-neighbour forecasting algorithm of simplex projection [43]. The optimal E will be evaluated and selected based on the forward performances of these nearby points in an embedding state space.

Therefore, by adopting the essential concept of Empirical Dynamic Modeling (EDM) and generalized Takens' Theorem [42], two manifolds are conducted based on the lagged coordinates of the two variables under evaluation, which are the attractor manifold M_Y constructed by Y_i and respectively, the manifold M_X by X_i. The causation will then be identified accordingly if the nearby points on M_Y can be employed for reconstructing observed X_i. Note that the correlation coefficient ρ is used for the estimates of cross map skill due to its wide acceptance and understanding. Additionally, leave-one-out cross-validation is considered a more conservative method and adopted for all evaluations in CCM.

2.2 Comparative Models

The results from CCM are compared with those from the time domain Granger causality test [44] and the frequency domain causality test [45, 46], which is an extension of the time domain Granger causality test that identifies the causality between different variables for each frequency.

3 Data

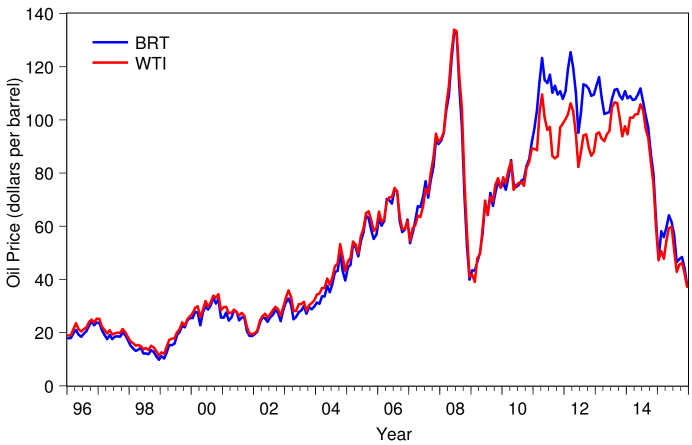


Figure 1: Monthly oil price data from 1996 to 2015.

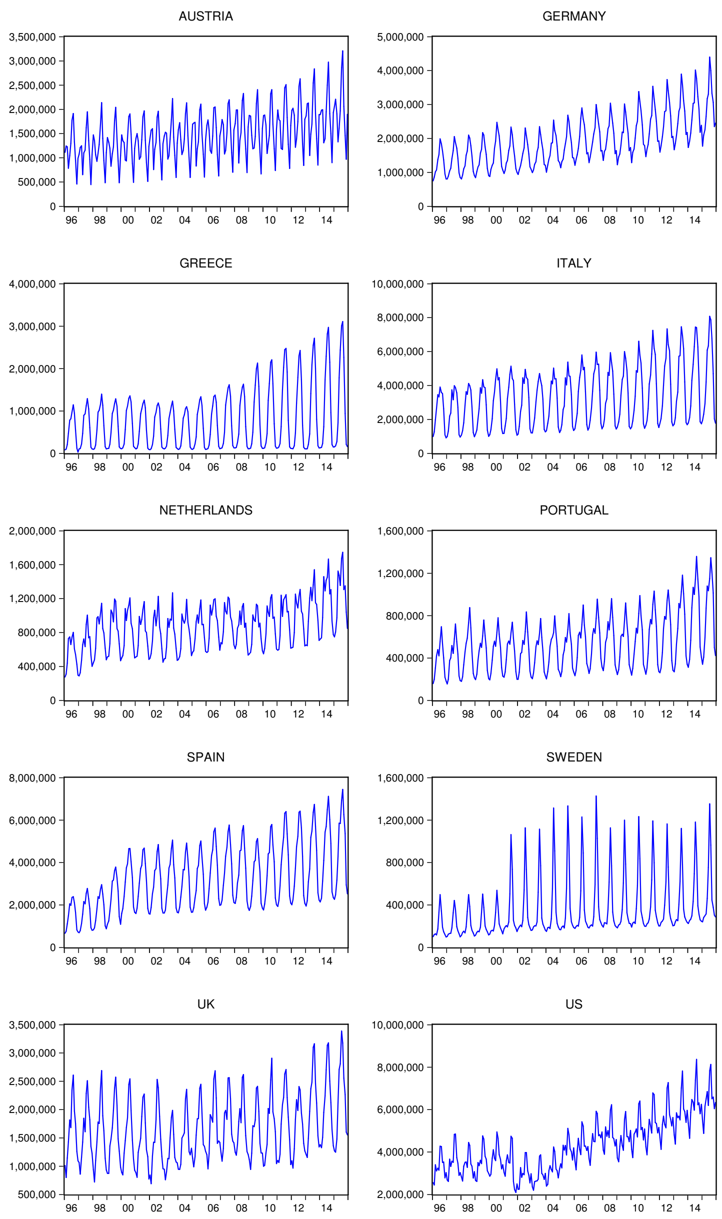


Figure 2: Monthly tourists arrivals data from 1996 to 2015 by countries.

The data used for this paper are at monthly frequency covering the period from January 1996 to December 2015 of both US and nine European countries, including Austria, Italy, Germany, Greece, Netherland, Portugal, Spain, Sweden, UK. In terms of the data, sample period and countries selections are considering the choice of [15], also due to such data is seldom used in the analysis of causal relationships between tourism demand and its influencing factors [14, 37]. US tourist arrivals were obtained from the US Department of Commerce National Travel & Tourism Office, while data for European countries were obtained from Eurostat. The data for oil prices include both West Texas

Intermediary Crude Oil Spot Price (WTI) and Europe Brent Spot Price (BRT) measured in the unit of dollars per barrel, and were obtained via the US Energy Information Administration [47].

Figure 1 shows the time series plots of the monthly oil prices, whilst, Figure 2 presents the time series plots of the monthly tourist arrivals by countries. It can be observed that the WTI and BRT oil prices are very similar except for a few months whereby the BRT reports a slightly higher price in relation to the WTI. The impacts of several structural breaks are also visible in Figure 1. In terms of the tourist arrivals data for the ten countries considered (Figure 2), it is evident that these series portray high levels of seasonality and increasing trends over time.

3.1 Descriptive Statistics

The summary of descriptive statistics are listed in Table 1. The data sets include 240 monthly observations for each variable. The descriptive statistics clearly confirm the similarity between BRT and WTI oil prices. In terms of tourist arrivals, all countries generally show almost identical levels of Skewness and Kurtosis except Sweden.

Table 1: Descriptive statistics for the data.

	Oil Prices							
	Obs	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis
BRT	240	56.41	49.22	132.72	9.82	35.24	0.47	1.85
WTI	240	54.78	49.06	133.88	11.35	31.19	0.40	1.89
	Tourist Arrivals							
	Obs	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis
Austria	240	1481894	1434455	3205966	446240	504448	0.39	3.21
Germany	240	1918394	1788583	4401682	747141	724552	0.75	3.29
Greece	240	765847	564523	3107955	29856	710611	1.11	3.66
Italy	240	3343953	3277084	8084209	907367	1709118	0.50	2.45
Netherland	240	870900	864200	1745779	275000	284180	0.34	2.79
Portugal	240	539796	522395	1359284	155438	256280	0.70	3.03
Spain	240	3229314	2934373	7443749	671109	1533209	0.51	2.42
Sweden	240	357927	239902	1428207	98357	289081	1.93	5.97
UK	240	1668020	1541000	3390515	692120	582239	0.59	2.64
US	240	4325374	4222034	8364940	2094287	1292787	0.59	2.88

3.2 Stationarity of data

In order to evaluate the stationarity of data, three different unit root tests including Kwiatkowski-Phillips-Schmidt-Shin (KPSS), augmented Dickey-Fuller (ADF) and Phillips and Perron (PP) are conducted and summarized in Table 2. The results overwhelmingly suggest trend stationary for all variables, whilst, the PP test indicates stationarity for a few countries in terms of the tourist arrivals data. In general, the variables are concluded non-stationary with one unit root.

Table 2: Unit root test results.

Variables	Series	Methods	None		Intercept		Intercept and Trend	
			Level	Decision	Level	Decision	Level	Decision
Oil Prices (240 Obs) 1996:1-2015:12	BRT	KPSS	———	———	1.675***(11)	I(1)	0.139*(11)	I(0)
		ADF	-10.284***(0)	I(1)	-10.264***(0)	I(1)	-10.294***(0)	I(1)
		PP	-10.279***(4)	I(1)	-10.258***(4)	I(1)	-10.283***(4)	I(1)
	WTI	KPSS	———	———	1.663***(11)	I(1)	0.166**(11)	I(1)
		ADF	-10.104***(0)	I(1)	-10.083***(0)	I(1)	-10.109***(0)	I(1)
		PP	-10.104***(0)	I(1)	-10.083***(0)	I(1)	-10.109***(0)	I(1)
Tourists Arrivals (240 Obs) 1996:1-2015:12	Austria	KPSS	———	———	1.458***(15)	I(1)	0.144*(27)	I(0)
		ADF	-3.938***(14)	I(1)	-16.637***(11)	I(1)	-17.093***(11)	I(0)
		PP	-49.801***(23)	I(1)	-9.945***(31)	I(0)	-10.345***(24)	I(0)
	Germany	KPSS	———	———	2.305***(9)	I(1)	0.115 (1)	I(0)
		ADF	-2.524***(13)	I(1)	-3.581***(13)	I(1)	-3.825***(13)	I(1)
		PP	-12.185***(16)	I(1)	-4.832***(5)	I(0)	-5.169***(0)	I(0)
	Greece	KPSS	———	———	0.755***(3)	I(1)	0.058(2)	I(0)
		ADF	-4.411***(11)	I(1)	-4.791***(11)	I(1)	-4.985***(11)	I(1)
		PP	-4.056***(5)	I(0)	-5.414***(6)	I(0)	-5.529***(6)	I(0)
	Italy	KPSS	———	———	1.079***(5)	I(1)	0.014(2)	I(0)
		ADF	-3.527***(13)	I(1)	-4.403***(13)	I(1)	-4.527***(13)	I(1)
		PP	-2.828***(3)	I(0)	-6.291***(4)	I(0)	-6.604***(4)	I(0)
	Netherland	KPSS	———	———	1.744***(8)	I(1)	0.084(4)	I(0)
		ADF	-2.976***(13)	I(1)	-3.496***(13)	I(1)	-3.503***(13)	I(1)
		PP	-14.361***(3)	I(1)	-5.952***(2)	I(0)	-6.548***(1)	I(0)
	Portugal	KPSS	———	———	1.653***(7)	I(1)	0.111(1)	I(0)
		ADF	-4.077***(12)	I(1)	-4.658***(12)	I(1)	-4.848***(12)	I(1)
		PP	-2.101**(6)	I(0)	-5.731***(5)	I(0)	-5.672***(6)	I(0)
	Spain	KPSS	———	———	1.991***(8)	I(1)	0.071(1)	I(0)
		ADF	-2.353**(12)	I(1)	-2.857*(12)	I(0)	-3.469**(13)	I(0)
		PP	-2.306**(4)	I(0)	-5.646***(4)	I(0)	-6.118***(5)	I(0)
	Sweden	KPSS	———	———	1.052***(2)	I(1)	0.161**(9)	I(1)
		ADF	-5.708***(13)	I(1)	-6.117***(13)	I(1)	-6.104***(13)	I(1)
		PP	-3.940***(14)	I(0)	-5.961***(19)	I(0)	-5.794***(24)	I(0)
	UK	KPSS	———	———	0.818***(5)	I(1)	0.090(3)	I(0)
		ADF	-4.889***(12)	I(1)	-4.981***(12)	I(1)	-5.196***(12)	I(1)
		PP	-10.446***(4)	I(1)	-5.821***(1)	I(0)	-6.387***(2)	I(0)
	US	KPSS	———	———	1.825***(11)	I(1)	0.392***(9)	I(1)
		ADF	-3.591***(12)	I(1)	-3.928***(12)	I(1)	-4.074***(12)	I(1)
		PP	-19.331***(6)	I(1)	-3.796***(8)	I(0)	-7.063***(8)	I(0)

[a] The *, ** and *** indicate significance at the 10%, 5% and 1% respectively.

[b] The critical values are as follows:(1)None: -2.574, -1.942 and -1.616 for ADF and PP at 1%, 5% and 10% level of significance, respectively; (2)Intercept: -3.457, -2.873 and -2.573 {0.739, 0.463, 0.347} for ADF and PP {KPSS} at 1%, 5% and 10% level of significance, respectively;(3)Intercept and Trend: -3.996, -3.428 and -3.137 {0.216, 0.146, 0.119} for ADF and PP{KPSS} at 1%, 5% and 10% level of significance respectively.

[c] Numbers in parentheses for ADF and PP tests indicates lag-lengths selected based on the Schwarz Information Criterion (SIC). For the KPSS test, based on the Bartlett kernel spectral estimation method, the corresponding numbers are the Newey-West bandwidth.

4 Causality Results

In this section, the causality tests are applied to tourist arrivals and both BRT and WTI oil prices respectively for each country. The corresponding results are summarized based on the different causality detection techniques employed.

4.1 Time domain granger causality

We begin by conducting the Granger causality test given its significance based on past literature and the empirical role in time series causality analysis. Note that all tests conducted satisfy the preconditions of time domain causality test with results by the corresponding optimal lag determined by a group of information criteria, including the Akaike Information Criterion (AIC) , SIC, Hannan Quinn Information Criterion (HQ) and Final Prediction Error Information Criterion (FPE). The results indicate that the null hypothesis of either direction of non-causality cannot be objected, which means that no causal link can be detected regardless of countries and types of oil price index. More specifically, the P-values of tests on tourist arrivals causing oil prices are relatively higher than the other way around for both BRT and WTI scenarios, also the values across countries vary. However, we find that the null hypothesis of non-causality cannot be rejected even at a 10% significance level for all countries considered. In brief, time domain Granger causality fails to detect any causal links between tourist arrivals and oil prices in a complex oil-tourism system for both US and nine European countries.

Table 3: Time domain granger causality test results.

Country	Oil Prices							
	BRT				WTI			
	→		←		→		←	
	P-value	Yes/No	P-value	Yes/No	P-value	Yes/No	P-value	Yes/No
Austria	0.68	No	0.56	No	0.81	No	0.34	No
Germany	0.52	No	0.27	No	0.29	No	0.17	No
Greece	0.54	No	0.36	No	0.46	No	0.44	No
Italy	0.60	No	0.98	No	0.67	No	0.74	No
Netherland	0.30	No	0.83	No	0.29	No	0.65	No
Portugal	0.38	No	0.41	No	0.72	No	0.31	No
Spain	0.62	No	0.24	No	0.54	No	0.12	No
Sweden	0.21	No	0.55	No	0.14	No	0.93	No
UK	0.63	No	0.95	No	0.53	No	0.82	No
US	0.48	No	0.85	No	0.53	No	0.48	No

Notes: → indicates tourist arrivals causes oil price;
← indicates oil price causes tourist arrivals.

4.2 Frequency domain causality

The frequency domain causality is then conducted for tourist arrivals and oil price data considering the possible causal link at specific frequencies. The results are briefly summarized in Table 4 due to the space limit[1]. It is noteworthy that the optimal lag-structures are maintained for all tests. The results show that no significant causality can be identified for any frequency, and the frequency domain test fails to prove the causal links between tourist arrivals and oil prices regardless of the countries.

Table 4: Frequency domain causality test results.

Country	Oil Prices			
	BRT		WTI	
	→	←	→	←
Austria	No	No	No	No
Germany	No	No	No	No
Greece	No	No	No	No
Italy	No	No	No	No
Netherland	No	No	No	No
Portugal	No	No	No	No
Spain	No	No	No	No
Sweden	No	No	No	No
UK	No	No	No	No
US	No	No	No	No

Notes: → indicates tourist arrivals causes oil price;
← indicates oil price causes tourist arrivals.

4.3 Convergent Cross Mapping (CCM)

In this subsection we present the findings following the initial application of CCM for the causality detection in oil-tourism studies, where tourist arrivals and oil prices in US and nine European countries

[1]Note that the detailed diagrams of testing results by countries, types of oil prices and directions of causality are available upon request.

are taken into consideration. Given the nonparametric nature of the CCM technique, we make no prior linear model assumptions as we seek for a better understanding of causal relationships in a complex dynamical system. Note that all the test results are obtained by the optimal embedding dimension respectively. More specifically, it is determined by the nearest neighbor forecasting performance using simplex projection; library size range is identical for the sake of further comparisons; and leave-one-out cross validation is applied for the best choice on library size with optimal performance. The results of CCM tests between tourist arrivals and oil prices are briefly summarized in Table 5[2].

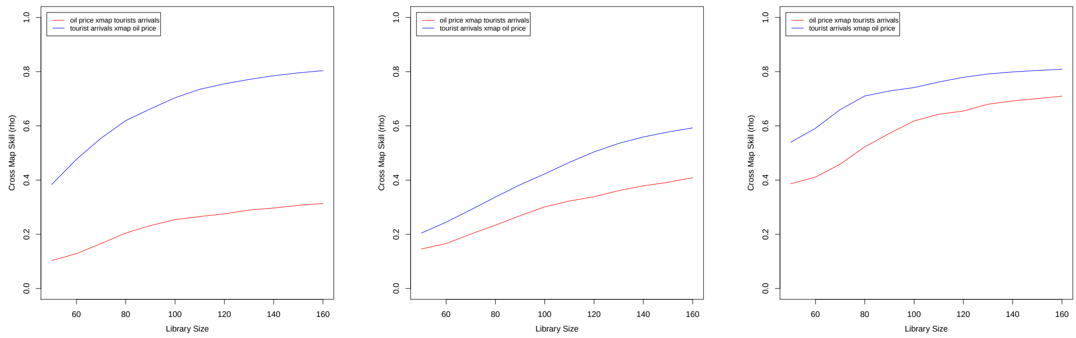
Table 5: CCM causality test results.

Country	**Oil Prices**			
	BRT		**WTI**	
	→	←	→	←
Austria	No	Yes	No	Yes
Germany	No	Yes	No	Yes
Greece	No	Yes	No	Yes
Italy	No	Yes	No	Yes
Netherland	No	Yes	No	Yes
Portugal	No	Yes	No	Yes
Spain	No	Yes	No	Yes
Sweden	No	Yes	No	Yes
UK	No	Yes	No	Yes
US	No	Yes	No	Yes

Notes: → indicates tourist arrivals causes oil price;
← indicates oil price causes tourist arrivals.

We find that significant causality is proved in general for all countries, as the test results strongly reflect a one-directional causal link from oil price to tourist arrivals. The results are very similar between BRT and WTI. For most of the countries, the cross map skill of oil price on tourist arrivals is also relatively high (still lower than the cross map skill of opposite direction). For instance the result of US in Figure 3, the red line presents relatively high cross mapping capability, however, as long as the other holds significant gap above, it indicates strong unidirectional causality. These results not only reflect the close significant relationship between these two tested variables regardless of the directions, but also confirm the findings in established literature. It is also observed that Austria shows the most significant causality from tourist arrivals on oil prices, whilst UK and US have slightly less significant outcomes on the average level (see Figure 4.3). Note that the improving trend in line with the increasing size of library is reasonable as larger size of data are used in cross validation for the cross map evaluation. The cross map skill from tourist arrivals to oil price (effect factor on cause factor) is much higher with a significant gap in between representing the level of causation from oil price on tourist arrivals. The greater the gap, the stronger the causality. In general, the CCM results prove one-directional causal link from oil price to tourist arrivals for both US and nine European countries.

[2]Note that the detailed diagrams of testing results by countries and types of oil prices are available upon request.



AUS UK US

Figure 3: CCM causality results for Austria, UK and US tourists arrivals and oil prices (WTI).

As an advanced nonparametric causality detection method, CCM outperforms the empirical methods with its sensitiveness and ability to accurately detect causality when faced with a complex system and less amount of data. More importantly, the tests show its significant ability of nonlinear causality detection and strong performance of identifying complex causal links in dynamical system. The results also indicate that CCM is a viable alternative for causality detection in the tourism industry.

5 Conclusion

This paper begins with the aim of investigating the causality between oil price and tourist arrivals in US and nine European countries. Both empirical and novel methods of causality detection are conducted to contribute towards explaining the impacts of oil price volatility on tourist arrivals across countries. More specifically, the advanced nonparametric causality technique CCM proves the existence of one-directional causality from oil prices to tourist arrivals for all countries when the empirical methods all fail to detect same.

This paper is also the first attempt at conducting CCM causality detection in oil-tourism studies. The consistent and significant evidences presented herewith in terms of for identifying significantly causal links across countries, CCM has proved to be a reliable and efficient method for causality detection when faced with complex and nonlinear scenarios as witnessed in oil-tourism studies. We believe that the findings of this research would motivate further research in relation to the development and increased application of CCM in tourism studies where the multivariate analysis of complex systems can be of utmost importance.

As the initial attempt of adopting advanced techniques in the causality analysis between oil price and tourist arrivals, this paper establishes consistent evidences across countries. By providing better understanding of the impacts from oil price on tourist arrivals, we hope to contribute on offering easy, efficient, data-driven and robust techniques for causality analyses of nonlinear and complex systems whilst assisting policy makings in terms of oil price volatility and economical activities closely related to tourism.

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