Terrorism in the behaviour of international monthly arrivals in the united states

This research paper investigates the tourism and terrorism nexus in the United States of America (USA) using monthly data from January 1996 until December 2016. We combine the Continuous Wavelet Transform (CWT) and the Vector Autorregression Model (VAR) to examine the dynamic relations between total international arrivals in the USA and the ratio of terrorist attacks per number of kills time series. Several interesting results ensued. Using wavelet analysis, we have found that, during 2000-2004, terrorist attacks increase precede a decrease on total arrivals in USA, adding to this result a longer-term impact of the terrorist attacks over total international arrivals in the USA. In addition, our causality test after the VAR model estimation provide evidence that terrorism explains the total international arrivals in the USA. To sum up these findings, we found a negative response of tourism to terrorist incidents.

PALABRAS CLAVE: Terrorism, USA Monthly Arrivals; Wavelet Analysis; Vector Autoregression; Causality

Este artículo de investigación estudia el nexo entre el terrorismo y el turismo en los Estados Unidos (EE. UU.) empleando datos mensuales desde enero de 1996 hasta diciembre de 2016. Combinamos el análisis Wavelet (continuous wavelet transform) y el modelo de vector autorregresivo (VAR) para examinar la relación entre dos series temporales: el número total de llegadas internacionales a Estados Unidos y el ratio de ataques terroristas por número de víctimas mortales. En este artículo se ofrecen diversos resultados interesantes. Usando el análisis Wavelet, hemos encontrado que, durante 2000-2004, un incremento en los ataques terroristas precede a un decrecimiento en el número total de llegadas a Estados Unidos, añadiendo a este resultado un mayor impacto de los ataques terroristas sobre el número total de llegadas a los Estados Unidos. Además, nuestro test de causalidad después del modelo de estimación VAR nos da evidencias de que el terrorismo explica las llegadas de turistas internacionales en los Estados Unidos. En definitiva, hemos encontrado una respuesta negativa del turismo a los ataques terroristas.

KEYWORDS: terrorismo, llegadas mensuales Estados Unidos, análisis Wavelet, causalidad.
1. Introduction

International travel and tourism is a significant contributor to economic growth and development, with worldwide growth in international tourist arrivals outpacing national income growth one out of every two years over the past 30 years (Baker, 2014).

In 2016, there were 1.235 billion international tourist arrivals worldwide, with a growth of 4% as compared to 1.186 billion in 2015. The ranking of United Nations World Tourism Organization showed that USA is in the second position by international tourist arrivals in 2016 with almost 75.6 millions arrivals. Moreover, travel and tourism’s total contribution to GDP in 2016 was 1,509.2 (US$bn), that represents 8.10% of total US$ GDP.

Terrorism is the premeditated use or threat to use violence by individuals or subnational groups to obtain a political or social objective through the intimidation of a large audience beyond that of the immediate victims (Enders and Sandler, 2011). This definition is consistent with other authors in the literature such as Hoffman (2006) or RAND (2012). Seddighi et al. (2001) and Stafford et al. (2002) state that the effects of terrorist attacks might cause political instability, which leads to the decline or disappearance of tourist arrivals in some tourist destinations.

Recent terrorist attacks and conflicts during the last 30 years, and the considerable current spread of ISIS, have rekindled the interest in the effects of terrorist attacks on the economy, and more particularly, on their consequences for tourism industry. Moreover, political and military relevance of the U.S. in the international scene, place this country as one of the main targets for terrorists at a global scale.

The literature confirm that terrorist attacks alter tourism demand, showing an increasing demand to cancel travel or holiday plans particularly after the 9/11 terrorist attack (Chen et al., 2004; Floyd et al., 2012; Kingsbury and Brunn, 2004).

In the past few years, since 1996, we have observed several terrorist events in USA that have been able to cause negative impact on tourism demand and alter the flow of international travel.

Terrorist attacks in the USA in September 2001, have had a negative and significant impact on tourism demand and international travel. It was precisely after September 11, 2001 that scholars in the tourism field showed increased interest in the topic.

The attacks induced substitution away from air travel generally and caused a shift in the preferences of tourists. The U.S. experienced an immediate and relevant drop in international arrivals after 9/11, specially from overseas. Some related factors, such the perception that U.S. visa policy became more restrictive in the wake of 9/11, may also have negative indirect effects on tourism arrivals. Hence, one terrorism event can become one country less attractive travel destination, damaging its image abroad (Alden, 2008).

The literature on modelling and forecasting arrivals time series is extensive. Both analytical and descriptive analysis discuss the economic consequences of terrorism, the effectiveness of the counter terrorism measures and the trends in terrorist attacks, among other issues (Sandler 2014). The existing literature about terrorism and tourism demand follows in general three lines: motives for which terrorist’s target tourism sector, solutions to minimize the risk of tourists and the consequences of terrorism on tourism demand (Pizam and Smith, 2000; Gaibulloev and Sandler, 2011; Baker, 2014).

Enders et al. (1992) provide empirical evidence on the link between terrorism and the
tourism sector for a sample of European countries and through a vector autoregressive analysis (VAR). Using an ARIMA model with a transfer function based on the time series of terrorist attacks in Austria, Greece and Italy, they find that a terrorist attack in Greece costs 23.4% of its annual tourism income for 1998.

Llorca-Vivero (2008), using bilateral tourism data to estimate a cross-sectional gravity model, studies the effect of terror attacks on tourist arrivals by analyzing tourism from the G-7 countries to 134 destinations. The research evaluated the differentiation between routine tourist flows and international arrivals following terrorism, pointing to a larger deviation in the developing countries. He finds that terrorism seriously damages the tourism industry, with particularly severe effects in developing countries. More recently, Robbins (2012) uses a cross-sectional gravity equation to measure the impact of terrorism on international tourist flows for eight European destination countries for the period 1991 to 2009. He shows that both the amount of terrorist attacks and the number of fatalities due to terrorism influence negatively tourism flows to European destination countries. Altindag (2014) analyses the effect of crime on tourism by using panel data that includes tourism flows to European countries. He finds that violent crime is negatively associated with tourist arrivals and tourism revenue.

If we look at the U.S. the impact of 9/11 on travel and tourism flows to the United States has been evaluated in several studies. Lee et al. (2005), evaluate the impact of the 9/11 attacks on the demand for air travel to the U.S. using a time series intervention model and found a significant overall drop in tourism demand. Similarly, Blunk et al. (2006) evaluate whether post 9/11 U.S. airline travel volume returned to its pre 9/11 trend and found that it had not by 2004. Bonham et al. (2006) quantify the initial impact of 9/11 on tourist arrivals to Hawaii and their recovery using a Vector Error Correction model (VECM). The results indicate that substitution away from foreign arrivals and towards US citizen arrivals took place in Hawaii and that the positive shock to US citizen arrivals offset the negative shock to foreign arrivals. The Hawaiian tourism industry had fully recovered from the 9/11 shock by 2003. Blalock et al. (2009), for example, quantify the increase in the number of auto driving fatalities due to substitution away from airline travel after 9/11. Despite the well-documented decline in foreign arrivals to the United States after 9/11, the negative post 9/11 trend in arrivals start to improve from 2002 to 2007.

In line with our data that corresponds to the terrorism events and number of kills occasioned by assassination, hijacking, kidnapping, barricade incident, bombing/explosion, armed assault, unarmed assault, facility/infrastructure attack, this article is focusing on a time period with several terrorist events, a situation that allows to analyze the magnitude and temporal scale of the relation between terrorism and tourism in a more differentiated way. Also, our results try to corroborate previous studies, taking into consideration the tested impact of 9/11 on U.S. tourism behavior. We also want to analyze if recent stability and terror problems in the U.S. shows a similar negative effect on tourism demand.

The contributions of this paper are threefold. First, to our knowledge this is the first paper that use a methodology based on a time-frequency technique that is able to analyze the evolution of the different frequency components of the time series overtime. Second, we use Granger causality test after VAR model estimation to examine the causality direction between both time series. Finally, we analyze the reaction of tourism over terrorism using the impulse response function from VAR model.
The paper proceeds as follows. Section 2 describes the methodology. Section 3 discusses our empirical results, showing the main evidences of the paper. Section 4 presents the conclusions of the study.

2. Methodology

2.1. Wavelet analysis

The wavelet transform offers localized frequency decomposition, providing information about frequency components. Wavelets have significant advantages over basic Fourier analysis when the series under study is stationary – see Gençay et al., (2002), Percival and Walden (2000) and Ramsey (2002). In our research, we use continuous wavelet analysis tools, mainly wavelet coherence, measuring the degree of local correlation between two-time series in the time-frequency domain, and the wavelet coherence phase differences.

2.1.1. The continuous wavelet transform

The continuous wavelet transform of a time series \( x(t) \), with respect to the wavelet \( \psi \), is a function \( WT_x(a, \tau) \) defined as:

\[
WT_x(a, \tau) = \int_{-\infty}^{\infty} x(t) \psi_{a, \tau}^*(t) dt
\]  

(1)

where \( WT_x(a, \tau) \) are the wavelet coefficients of \( x(t) \) at a certain scale \( a \) and a shift \( \tau \), where,

\[
\psi_{a, \tau}^* = \frac{1}{\sqrt{a}} \psi^* \left( \frac{t-\tau}{a} \right)
\]  

(2)

is the complex conjugate of the wavelet function \( \psi \). The parameter \( a \) is a scaling factor that controls the stretching factor of the wavelet and \( \tau \) is a location parameter in time. Then, \( WT_x(a, \tau) \) will be a matrix of time series. The scaling factor \( a \) is a positive real number that simply means stretching it (if \( a > 1 \)), or compressing it (if \( a < 1 \)). If \( a \) is positive, we assume that we are using an analytic or progressive wavelet, i.e., its Fourier transform is defined by the positive frequency axis, \( \Psi(\omega) = 0 \) when \( \omega < 0 \).

The lower the value of the scaling factor, the more higher frequency components are reflected in the continuous wavelet transform, thus we are dealing with the short-run components of the signal. As the scaling factor increases, we are dealing with lower frequency components of the time series, focusing on the long-run components. Then, the continuous wavelet transform is a multidimensional transform; from one-time series we obtain a matrix of time series that show different frequency components (depending on the scaling factor) of the original one.

If the wavelet function \( \psi \) is complex, then the wavelet transform \( WT_x(a, \tau) \) will also be complex, with amplitude, \( |WT_x(a, \tau)| \), and phase, \( \phi_x(a, \tau) \). The real part of the wavelet transform...
transform, $Re\{WT_x\}$, and its imaginary part, $Im\{WT_x\}$ define the phase or phase-angle of the wavelet transform:

$$\phi_X=\text{Arctan}\left(\frac{Im\{WT_x\}}{Re\{WT_x\}}\right) \quad (3)$$

The phase of a given time-series $x(t)$ is measured in radians, ranging from $-\pi/2$ to $+\pi/2$. Then, the phase is also a matrix containing the angle of each frequency component of the original time series. The phase will be used to extract conclusions of the synchronism between two time series, applying the wavelet coherency and the phase difference between time series (Aguiar-Conraria and Soares, 2011a,b and 2014).

The wavelet or mother wavelet used to analyze the time series must satisfy certain technical conditions to provide effective time-frequency location properties (Daubechies, 1992). First, it has to be a function of finite energy, $\int_{-\infty}^{+\infty} \psi(t) dt=0$. There are many different wavelet families, but the election of a certain wavelet will depend on the application itself.

Related to time localization properties, we can normalize the wavelet function so that $\int_{-\infty}^{+\infty} |\psi(t)|^2 dt=1$. $|\psi(t)|^2$ defines a probability density function, and therefore we can obtain the mean, $\mu_{\psi}$, and the standard deviation, $\sigma_{\psi}$, of this distribution. They are called the center and the radius of the wavelet, respectively. If we consider the Fourier transform of the mother wavelet, $\Psi(\omega)$, in a similar way we can calculate its mean and standard deviation, $\mu_{\Psi}$ and $\sigma_{\Psi}$.

These quantities define the Heisenberg box in the time-frequency plane: $[\mu_{\psi}-\sigma_{\psi},\mu_{\psi}+\sigma_{\psi}] \times [\mu_{\Psi}-\sigma_{\Psi},\mu_{\Psi}+\sigma_{\Psi}]$. We say that $\psi$ is localized around the point $(\mu_{\psi},\mu_{\Psi})$ of the time–frequency plane with an uncertainty given by $\sigma_{\psi} \beta \sigma_{\Psi}$. In our context, the Heisenberg’s uncertainty principle establishes that $\sigma_{\psi} \sigma_{\Psi} \geq 1/2$.

The Morlet wavelet,

$$\psi(t)=\pi^{-1/4} e^{i\omega_0 t} e^{-t^2/2} \quad (4)$$

is a complex valued wavelet, so we will be able to measure the synchronism between two-time series. This wavelet has optimal time–frequency concentration, in the sense that $\sigma_{\psi} \sigma_{\Psi} = 1/2$. Therefore, using this wavelet, we have the optimum trade off between time and frequency resolution. On the other hand, the Morlet can be considered as a wavelet (with finite energy, defined as before) when the frequency parameter $\omega_0 = 6$. For this value of the Morlet wavelet, the wavelet scale, $a$, satisfies the inverse relation $f \approx 1/a$, as the rest of the most used mother wavelets.

2.1.2. Wavelet and cross wavelet power spectrum, and wavelet coherency

The wavelet power spectrum (WPS) or the scalogram of a time series $x(t)$, as it is called, is the squared amplitude of the wavelet transform, that is: $WPS_x (a,\tau) = |WT_x (a,\tau)|^2$. The wavelet power spectrum lets us know the distribution of the energy (spectral density) of a time-series across the two-dimensional time–frequency representation.

While the wavelet power spectrum shows the variance of a time-series in the time-
frequency plane, the cross wavelet power spectrum (CWPS) of two time-series \( x(t) \) and \( y(t) \) shows the covariance between these time series in the time-frequency plane:

\[
CWPS_{xy}(a,\tau) = |WT_x(a,\tau) WT_y(a,\tau)^* | \tag{5}
\]

where * represents the complex conjugate, as before.

Therefore, the complex wavelet coherency between two time series \( x(t) \) and \( y(t) \) is defined as the ratio of the cross-spectrum and the product of the power spectrum of both series:

\[
WCO_{xy} = SO(WT_x(a,\tau) WT_y(a,\tau)^* )/\sqrt{(SO(|WT_x(a,\tau)|^2) SO(|WT_y(a,\tau)|^2 ))} \tag{6}
\]

where \( SO \) is a smoothing operator in both time and scale. Without the smoothing operator, the wavelet coherency would be always one for all times and scales (see Aguiar-Conraria et al. (2008) for details).

As the \( WCO_{xy} \) is a matrix of complex time series, we can split it again into amplitude and phase, \( WCO_{xy} = |WCO_{xy}| e^{i\phi_{xy}} \). The amplitude matrix is the wavelet coherency, \( WC_{xy} \) and the angle \( \phi_{xy} \) is called the phase difference between both time series:

\[
\phi_{xy} = \arctan((\text{Im}\{WCO_{xy}\} )/(\text{Re}\{WCO_{xy}\} )) \tag{7}
\]

\( \phi_{xy} \) is the phase difference between time series \( x(t) \) and \( y(t) \), and tells us about the synchronism between those time series. \( \phi_{xy} \) ranging from \(-\pi\) to \(\pi\).

On the one hand, if \( \phi_{xy} = 0 \) then both time series move in phase. This will mean that both time series increase or decrease their values at the same time. If \( \phi_{xy} \in (-\pi/2,0) \), they move in phase but the time series \( x(t) \) is leading; if \( \phi_{xy} \in (0,\pi/2) \), the time series \( y(t) \) is leading. Therefore, in these cases we can find that one time series anticipates the increase or decrease of the other one. On the other hand, a phase difference of \( \pi \) or \(-\pi\) indicates an anti-phase relation, when one time series increases, the other one is decreasing in time. Finally, if \( \phi_{xy} \in (-\pi/2,\pi/2) \), both time series are out of phase but \( x(t) \) is leading; if \( \phi_{xy} \in (\pi/2,\pi) \), \( y(t) \) is leading. In this case this means that one time series has a time delay with respect to the other.

### 2.1.3. Significance tests, Monte Carlo simulations

To check the statistical significance of the wavelet coherency, \( WC_{xy} \), we rely on Monte Carlo simulations (Schreiber and Schmitz, 1996). We model each time series as an ARMA \((p, q)\) process where \( p = q = 1 \), with no pre-conditions. Then we assess the statistical significance of the amplitude, not of the phase. The phase difference is not tested as there is no agreement in the scientific community about how to define the procedure. We should only take into account the phase difference when the amplitude of the wavelet coherency is statistically significant.

### 2.2. Vector auto-regression model

Sims (1980) presented the vector auto regression model (VAR) for the dynamic analysis
of the economic system. The VAR model treats all of the variables as endogenous, and evaluates the estimation of the dynamic interaction between the economic variables. The VAR model can be expressed as follows:

\[ y_t = \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \varepsilon_t, t=1,2,\ldots,T \]

where \( y_t \) is a k-dimensional endogenous variables column vector, \( p \) is the lag length, and \( T \) is the number of sample.

### 2.2.1. Causality

The Granger causality test is used after the VAR model estimation to examine the causality direction two stationary series \( x_t \) and \( y_t \). The linear causality test is based on a bivariate vector autoregressive (VAR) representation of the two series, as follow:

\[
\begin{align*}
  x_t &= a_1 + \sum_{i=1}^{k} a_i x_{t-i} + \sum_{i=1}^{k} \beta_i y_{t-i} + \varepsilon_{1t} \\
  y_t &= a_2 + \sum_{i=1}^{k} \gamma_i x_{t-i} + \sum_{i=1}^{k} \delta_i y_{t-i} + \varepsilon_{2t}
\end{align*}
\]

where \( k \) is the lag length of the \( x_t \) and \( y_t \) variables. We can thus test null hypothesis: (1) \( y \) does not cause \( x \), which is represented as \( H_0^y = y_1 = \cdots = y_k = 0 \). In the first case, causality runs from \( y \) to \( x \) when the null is rejected; in the second case, causality runs from \( x \) to \( y \) when the null is rejected; and finally, bivariate causality means that both hypotheses are rejected. The test statistic for these hypotheses has a standard Chi-squared distribution.

### 3. Empirical results

#### 3.1. Data

Based on the available data, we examine the total number of international arrivals in the USA and the ratio of terrorist attacks per number of kills registered by month over the period 1996:01-2016:12. The total international arrivals data was collected from the National Travel and Tourism Office (NTTO).

Total number of terrorist events and number of kills by month was obtained from Global Terrorism Database (National Consortium for the Study of Terrorism and Responses to
Terrorism (START), 2015), which records both domestic and transactional terrorism\(^1\).

Figure 1 shows the comparison between both time series.

**Figure 1: Total international arrivals in the USA and the ratio of terrorist attacks per number of kills (National Consortium for the Study of Terrorism and Responses to Terrorism; START, 2015).**

3.2. **Empirical Results**

3.2.1. **Continuous Wavelet Transform**

We use Continuous Wavelet Transform (CWT) to discover patterns or hidden information between the both time series.

We first estimated the wavelet coherency between the ratio of terrorist attacks per number of kills and total international arrivals in the USA. This study relied on Monte Carlo simulation to test if the similitude of the wavelet coherency is statistically significant. Then the complex wavelet coherence matrices were computed between a surrogate for ratio and a surrogate for the total international arrivals time series. A total of 1000 simulations were modeled on both time series as an ARMA \((p, q)\) process, with no preconditions on \(p\) and \(q\), with \(p = q = 1\).

The wavelet coherency was estimated for frequencies corresponding to periods between

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\(^1\) Type of recorded events: assassination, hijacking, kidnapping, barricade incident, bombing/explosion, armed assault, unarmed assault, facility/infrastructure attack.)
1.5 and 8 years.

Figure 2: Wavelet coherency and phase difference between the ratio of terrorist attacks per number of kills and total international arrivals in the USA. The contour designates the 5% significance level. Left: Wavelet coherency between the ratio of terrorist attacks per number of kills and total international arrivals in the USA. Right: Phase difference between the ratio of terrorist attacks per number of kills and total international arrivals in the USA at 1.5-4 year (top) and 4.5-8 year (bottom) frequency bands.

Figure 2 displays the empirical results. The left panel (a) has the wavelet coherency between the ratio of terrorist attacks per number of kills and total international arrivals in the USA. The right has the phase differences: on the top (b) is the phase difference in the 1.5-4 year frequency band; at the bottom (c) is the phase difference in the 4.5-8 year frequency band. The regions surrounded by the black contour are the high coherency regions with significant values at 5%.

Analyzing the wavelet coherency between the ratio of terrorist attacks per number of kills and total international arrivals in the USA, we appreciate that the most important region with higher coherency is between 2000 and 2004. The phase difference analysis is focused on two frequency bands: 1.5-4 and 4.5-8 years.

To analyze the wavelet coherency graph, we have to focus on the regions of high coherency of the chart. In those regions, we can observe the phase difference of the frequency band to extract some conclusions.

In the 1.5-4 and 4.5-8 year band, we identify a region of high coherency between 2000 and 2004, in the frequency bands between 2.5 and 3.5 years and between 5 and 6.5 years, respectively with a corresponding phase difference in these bands between $-\pi$ and $-\pi/2$. These results suggest that terrorist attacks per number of kills and total international arrivals in the USA time series are out of phase (negative correlated) with terrorism leading. This suggest that terrorist attacks increase precede a decrease on total international arrivals in the USA.

From this wavelet coherency figure, we can observe a change across time in the common frequency bands between terrorism and total international arrivals in the USA; Lower frequency

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2. Coherency ranges from blue (low coherency) to red (high coherency). The cone of influence is shown with a thick line, which is the region subject to border distortions.
between the years 2000-2004 indicates a long-term component, i.e. a lower frequency band of approximately 7 to 8 years and 4.5 to 5.5 years, respectively, suggest a longer-term impact of the terrorist attacks over total international arrivals in the USA.

### 3.2.2. Unit roots methods

The VAR model is implemented to explore the terrorist attacks and international arrivals in the USA nexus.

Initially, a unit root test should be used to examine the statistical properties of the time series that are used in the VAR model. We select the Augmented Dickey-Fuller test (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin test (KPSS) to obtain robust results. Table 1 displays the results, which clearly suggest that the ratio of terrorist attacks per number of kills time series is stationary I(0) and total international arrivals in the USA is nonstationary I(1). These methods indicate that is important to do the first differences of total international arrivals time series to construct the VAR model.

**Table 1: Notes: TS – test statistic; C – Constant; T – trend.**

<table>
<thead>
<tr>
<th></th>
<th>ADF</th>
<th>KPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>C</td>
<td>C&amp;T</td>
</tr>
<tr>
<td>TS</td>
<td>p-value</td>
<td>TS</td>
</tr>
<tr>
<td>Total Arrivals USA</td>
<td>-0.272169</td>
<td>0.9256</td>
</tr>
<tr>
<td>Ta*n Kills</td>
<td>-15.78568</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

### 3.2.3. Granger causality test

The Granger causality test is used first to examine the interactions between the ratio constructed by terrorist attacks and number of kills and total international arrivals in the USA. The Granger causality test is based on VAR model with variables placed in the following order: first difference of total arrivals and ratio of terrorist attacks per number of kills.

The Granger causality test results of these two time series are shown in Table 2.
Table 2: The Granger causality test results for the VAR model

<table>
<thead>
<tr>
<th>Dependent</th>
<th>Independent</th>
<th>Chi-sq</th>
<th>Prob</th>
</tr>
</thead>
<tbody>
<tr>
<td>D(Total_arrivals)</td>
<td>Ta_nkill</td>
<td>40.97152</td>
<td>0.0001</td>
</tr>
<tr>
<td>Ta_nkill</td>
<td>D(Total_arrivals)</td>
<td>9.892468</td>
<td>0.7027</td>
</tr>
</tbody>
</table>

After obtaining the results, we only found causality from terrorism to international arrivals. We can conclude that the total international arrivals in the USA has not a bidirectional Granger causality relation with terrorism. Only the terrorism explains the total international arrivals in the USA.

3.2.4. Impulse response to the total international arrivals in the USA

Finally, for the asymmetric effect of the total arrivals in USA, we need to identify the response direction of the USA tourism to the terrorism events.

Based on the VAR model, the impulse response function could offer refined insight into the response of the USA tourist arrivals to terrorism events in the same region in terms of the response amplitude and direction. In Figure 3, the upper row is the responses of the total international arrivals in the USA to the terrorism events, and the second row, at the bottom, is the responses of the terrorism events to the total international arrivals in the USA.

Figure 3: Impulse response function of the total international arrivals in the USA VAR model
The shocks in this study are measured by the Cholesky one standard deviation innovations (Hamilton, 1994). Figures 3 shows the ways in which total international arrivals in the USA responds to the shock occurring with the terrorist attacks in USA over 10 monthly periods. In the case of total arrivals, a shock in the variable itself (see the top left panel in Figure 3) will have a relatively larger impact on the current level of arrivals and this impact will gradually die off and disappear after 10 periods (10 months). The top right panel of Figure 3 show that tourist arrivals respond negatively to the shock in terrorist events and number of kills and the momentum of this impact takes about 3 months to disappear.

4. Conclusions

This paper contributes to the literature on how terrorist attacks affect the behavior of international monthly arrivals in United States by studying its dynamic in the time-frequency domain. Assuming that there is empirical evidence on the link between terrorism and the tourism sector (Enders et al., 1992), we combine the Continuous Wavelet Transform (CWT) and the Vector Autoregression Model (VAR) to examine the dynamic relations between both time series. In this research, we have analyzed the number of terrorist events per number of kills by month from Global Terrorism Database (National Consortium for the Study of Terrorism and Responses to Terrorism (START), 2015) and its effects on international monthly arrivals in United States.

The first step in this research paper has been to analyze the wavelet coherency. We appreciate that the regions with higher coherency, which are also statistically significant (the 5% significance level estimated from Monte Carlo simulations), are between 2000 and 2004.

The phase information about this period is located, 2000-2004, is in the frequency bands between 2.5 and 3.5 years and between 5 and 6.5 years, respectively, with a corresponding phase difference in these bands between $-\pi$ and $-\pi/2$, suggesting a negative relation between terrorist attacks and international arrivals in USA, suggesting that terrorist attacks increases precede a decrease on total international arrivals, adding a long term impact of the terrorist attacks over tourism in this period.

In the second part of this research we have employed a causality test after the VAR model estimation to provide evidence that terrorism explains the total international arrivals in the USA. Finally, using the impulse response function from VAR estimation, we have found a negative response of tourism to terrorist incidents.

References


