Blurring the Lines between Tourism and Terrorism in Western Europe

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Introduction

This project will explore the relationship between tourism and terrorism within Western Europe. In the past several years, developed countries have seen an increase in the number of terrorist attacks, especially in big cities, that have caught worldwide attention. With the popularity of online media and news outlets, almost everyone has accesss to information on terrorism and terrorist activities, and could possibly inherit widespread paranoia from these events. From firsthand accounts, hearing about these violent events have discouraged some people from visiting the region, although this would not be an accurate judgment of all people. Because of this, I would like to utilize a more legitimate and accurate tool, Python, to discover if these word of mouth comments hold some weight to a greater conversation on the perception of violence, safety and future trends of tourism.

My final goal is to provide an idea on **if** terrorism is related to tourism, not necessarily proving that there is a direct relationship between the two variables. The project is to simply manipulate the data, and any conclusion is based solely on the given information below. If there is any relationship this is not to say that there is a cause and effect; finding no relationship is entirely possible as well.

Methodology

In executing this project, information on two main datasets will have to be extracted:

Data on terrorism was extracted from the Global Terrorism Database (GTD) (https://www.start.umd.edu/gtd/). This is the only comprehensive database on all recorded terrorist activities in every country starting from 1970. According to GTD, a terrorist attack is considered an intentional violent attack from subnational actor(s) in order to attain political, social, religious, or economic goals. State-sponsored terrorism is not included in this overview. Victims are considered any person(s), specified group of person(s), institutions, government, business, private and public properties. Important factors to consider are the country names, region, year, and individual event ids. The GTD website provides the data only in form of excel files, which have to be downloaded given a valid e-mail address, preferably from an academic institution.

Data on international tourism was extracted from a database (https://data.worldbank.org/indicator/ST.INT.ARVL?end=2016&locations=CA&start=2005) at The World Bank (http://www.worldbank.org/), which covers various other statistical information by country and development priority. The organization has amassed a library of development knowledge through data-driven research. Tourism rates for this particular database are calculated by the number of internationl arrivals into each country per year. Data is obtained through the World Bank's API.

The relevant data on terrorism came in two excel files; the first file records all terrorist attacks from 1995-2012 and the second file that covers years 2013-2016. Both would need to be concatenated, and stripped down to the country, region, year, and event id. Using this information, the six countries in Western Europe that have had the most terrorist attacks will be used to observe their rates of change in terrorism and tourism from 2005 to 2016.

Main sections will include:

- Cross referencing the number of tourists and number of terrorist attacks over a 12 year period. The countries that are being investigated will be those in Western Europe, that have had the highest number of terrorist attacks in the past decade and a half.
- Measuring growth rates by calculating increasing or decreasing quantities of tourists and attacks.
- In visualizing the data, necessary graphs will include comparing rates of change and finding their regressions.

Important variables:

- Country Name
- Year
- Region
- Event Id
- Change in number of tourists (percentage and rate)
- Change in number of terrorist attacks (percentage and rate)

Access to Data Cleaning

In [136]:
```
import pandas as pd   # to create dataframes
import matplotlib.pyplot as plt   # to plot graphs
import numpy as np   # for numerical calculations
import wbdata   # to extract data from World Bank
import seaborn as sns    # to plot regression charts
from linearmodels.panel import PanelOLS  # for regression analysis

%matplotlib inline
```

Terrorism Data: Cleaning and Finding Rate of Change

There are two files extracted straight from GTD. Since these files are too large to upload directly, they had to be split into five smaller files and uploaded independently. These files are uploaded to GitHub, which then are extracted. They will all be concatenated into one large dataframe. There are 135 different columns for each file, for which this project only requires four: country name, year, eventid, and region.

In [107]:
```
ta_1 = "https://raw.githubusercontent.com/sl4655/Data_Bootcamp_Final_Project/master/GTD_05to09.csv"

df_ta_1 = pd.read_csv(ta_1, low_memory=False)

df_ta_1.head()

# this is the data set that covers all attacks from 2005 to 2009
```

Out[107]:

	eventid	iyear	imonth	iday	approxdate	extended	resolution	country	country_txt	region	...	addnotes	
0	2.010000e+11	2005	1	1	NaN	0	NaN	95	Iraq	10	...	NaN	Britis Secu Guar Killec Suici Atta..
1	2.010000e+11	2005	1	1	NaN	1	NaN	159	Peru	3	...	The outcome of hostage situation was unknown, ...	Peru Troop Laun Assa Rebe Held.
2	2.010000e+11	2005	1	1	NaN	0	NaN	45	Colombia	3	...	The mayor of Tame, Alfredo Guzman Tafur, said ...	"FAR Rebe Seve Peop Tame
3	2.010000e+11	2005	1	1	NaN	0	NaN	28	Bosnia-Herzegovina	9	...	NaN	"Girl Wour in Bo Serb Repu Gren
4	2.010000e+11	2005	1	1	NaN	0	NaN	92	India	6	...	NaN	"Milit Trigg Blast Kash Anan

5 rows × 135 columns

In [108]:
```
ta_2 = "https://raw.githubusercontent.com/sl4655/Data_Bootcamp_Final_Project/master/GTD_10to12.csv"

df_ta_2 = pd.read_csv(ta_2, low_memory=False)

df_ta_2.head()

# this is the data of all attacks from 2010 to 2012
```

Out[108]:

	eventid	iyear	imonth	iday	approxdate	extended	resolution	country	country_txt	region	...	addnotes	
0	2.010000e+11	2010	1	1	NaN	0	NaN	4	Afghanistan	6	...	The available sources listed the fatalities fo...	Press Afgha Road Bomb
1	2.010000e+11	2010	1	1	NaN	0	NaN	153	Pakistan	6	...	NaN	Jane' Intelli "Pro-T Milita
2	2.010000e+11	2010	1	1	NaN	0	NaN	153	Pakistan	6	...	NaN	Raza Dawn Held Involv
3	2.010000e+11	2010	1	1	NaN	0	NaN	153	Pakistan	6	...	This was one of three related attacks (cf. 201...	Press "Milita Raze Scho Nort...
4	2.010000e+11	2010	1	1	NaN	0	NaN	153	Pakistan	6	...	This was one of three related attacks (cf. 201...	Press "Milita Raze Scho Nort...

5 rows × 135 columns

In [109]:
```
ta_3 = "https://raw.githubusercontent.com/sl4655/Data_Bootcamp_Final_Project/master/GTD_13to14.csv"

df_ta_3 = pd.read_csv(ta_3, low_memory=False)

df_ta_3.head()
```

Out[109]:

	eventid	iyear	imonth	iday	approxdate	extended	resolution	country	country_txt	region	...	addnotes	s
0	2.013010e+11	2013	1	1	NaN	0	NaN	153	Pakistan	6	...	NaN	"Expl devic defus Bann The N ...
1	2.013010e+11	2013	1	1	NaN	0	NaN	95	Iraq	10	...	Casualty numbers for this incident represent a...	"Dea bomb leave destr in Kirku
2	2.013010e+11	2013	1	1	NaN	0	NaN	95	Iraq	10	...	Casualty numbers for this incident represent a...	"Dea bomb leave destr in Kirku
3	2.013010e+11	2013	1	1	NaN	0	NaN	95	Iraq	10	...	Casualty numbers for this incident conflict ac...	"2 co woun by explo mid Kirku Aswa
4	2.013010e+11	2013	1	1	NaN	0	NaN	153	Pakistan	6	...	NaN	"Trag avert 5kg b defus near

5 rows × 135 columns

In [110]:
```
ta_4 = "https://raw.githubusercontent.com/sl4655/Data_Bootcamp_Final_Project/master/GTD_14to15.csv"

df_ta_4 = pd.read_csv(ta_4, low_memory=False)

df_ta_4.head()
```

Out[110]:

	eventid	iyear	imonth	iday	approxdate	extended	resolution	country	country_txt	region	...	addnotes	sc
0	2.014040e+11	2014	4	24	NaN	0	NaN	95	Iraq	10	...	Casualty numbers for this incident conflict ac...	"Suici attacl Iraq k at lea 11 ...
1	2.014040e+11	2014	4	24	NaN	0	NaN	95	Iraq	10	...	Casualty numbers for this attack represent a d...	"20 perso woun in Kirkul Aswa Iraq,..
2	2.014040e+11	2014	4	24	NaN	0	NaN	228	Yemen	10	...	NaN	"Yem Roun of Secu Incide 25 April..
3	2.014040e+11	2014	4	24	NaN	0	NaN	95	Iraq	10	...	NaN	"Iraq: Roun of Secu Incide 22-28 Apr...
4	2.014040e+11	2014	4	24	NaN	0	NaN	95	Iraq	10	...	Casualty numbers for this incident conflict ac...	"25 ki in attacl in Irac Xinhu Gen..

5 rows × 135 columns

In [111]:
```
ta_5 = "https://raw.githubusercontent.com/sl4655/Data_Bootcamp_Final_Project/master/GTD_15to16.csv"

df_ta_5 = pd.read_csv(ta_5, low_memory=False)

df_ta_5.head()
```

Out[111]:

	eventid	iyear	imonth	iday	approxdate	extended	resolution	country	country_txt	region	...	addnotes	sc
0	2.015060e+11	2015	6	21	NaN	0	NaN	95	Iraq	10	...	NaN	"Iraq: Roun of Secu Incide 16-22 Jun...
1	2.015060e+11	2015	6	21	NaN	0	NaN	95	Iraq	10	...	NaN	"Iraq: Roun of Secu Incide 16-22 Jun...
2	2.015060e+11	2015	6	21	NaN	0	NaN	95	Iraq	10	...	Casualty numbers for this incident conflict ac...	"21/0 20:46 Bomb attack near Iraqi capita
3	2.015060e+11	2015	6	21	NaN	0	NaN	95	Iraq	10	...	NaN	"Iraq: Roun of Secu Incide 16-22 Jun...
4	2.015060e+11	2015	6	21	NaN	0	NaN	95	Iraq	10	...	Casualty numbers for this incident conflict ac...	"21/0 20:46 Bomb attack near Iraqi capita

5 rows × 135 columns

In [112]:
```
df_ta = pd.concat([df_ta_1, df_ta_2, df_ta_3, df_ta_4, df_ta_5])

df_ta.head()

# I am combining the two data sets, one on top of another to make one larger one
```

Out[112]:

	eventid	iyear	imonth	iday	approxdate	extended	resolution	country	country_txt	region	...	addnotes	
0	2.010000e+11	2005	1	1	NaN	0	NaN	95	Iraq	10	...	NaN	Britis Secu Guar Killec Suici Atta...
1	2.010000e+11	2005	1	1	NaN	1	NaN	159	Peru	3	...	The outcome of hostage situation was unknown, ...	Peru Troop Laun Assa Rebe Held.
2	2.010000e+11	2005	1	1	NaN	0	NaN	45	Colombia	3	...	The mayor of Tame, Alfredo Guzman Tafur, said ...	"FAR Rebe Seve Peop Tame
3	2.010000e+11	2005	1	1	NaN	0	NaN	28	Bosnia-Herzegovina	9	...	NaN	"Girl Woun in Bo Serb Repu Gren
4	2.010000e+11	2005	1	1	NaN	0	NaN	92	India	6	...	NaN	"Milit Trigg Blast Kash Anan

5 rows × 135 columns

In [113]:
```
df_ta.set_index(['iyear'], inplace = True)

# I am setting the index to year as it is also the common index in the World Bank tourism data.
```

In [114]:
```
world= df_ta.loc[[2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016], ['country_txt'
, 'region_txt', 'eventid']]

# these are the years I want to look at (2005 - 2016), as well as the relevant tags: the country name, th
e regions, and the specific attack id.

world.head()
```

Out[114]:

	country_txt	region_txt	eventid
iyear			
2005	Iraq	Middle East & North Africa	2.010000e+11
2005	Peru	South America	2.010000e+11
2005	Colombia	South America	2.010000e+11
2005	Bosnia-Herzegovina	Eastern Europe	2.010000e+11
2005	India	South Asia	2.010000e+11

In [115]:
```
we = world.loc[world['region_txt'] == "Western Europe"]

# more specifically, I want to look at countries in Western Europe

we.head(10)
```

Out[115]:

	country_txt	region_txt	eventid
iyear			
2005	United Kingdom	Western Europe	2.010000e+11
2005	France	Western Europe	2.010000e+11
2005	Greece	Western Europe	2.010000e+11
2005	Sweden	Western Europe	2.010000e+11
2005	Spain	Western Europe	2.010000e+11
2005	France	Western Europe	2.010000e+11
2005	France	Western Europe	2.010000e+11
2005	Spain	Western Europe	2.010000e+11
2005	Spain	Western Europe	2.010000e+11
2005	Spain	Western Europe	2.010000e+11

In [116]:
```
new = we.groupby(["iyear", "country_txt"])[['eventid']].count()

# Using the groupby and count method,I want to calculate the number of terrorist attacks by grouping them
 into year and specific country.

display(new.head(10))
```

		eventid
iyear	**country_txt**	
2005	**France**	33
	Germany	3
	Greece	6
	Italy	6
	Spain	24
	Sweden	3
	United Kingdom	25
2006	**Austria**	1
	France	34
	Germany	4

In [117]:
```
we_ta = new.unstack(fill_value=0.0).sum(level=1, axis=1)

# this is important for organization, and to replace any NaN with 0.0.

we_ta.sum().sort_values(ascending=False).head(6)

# I want to find the six countries in Western Europe with the highest rates of terrorist activities.
```

Out[117]:
```
country_txt
United Kingdom    728.0
Greece            435.0
France            269.0
Germany           148.0
Ireland           147.0
Spain             133.0
dtype: float64
```

Once we have found how the top six countries in Western Europe that have most terrorist activity, this data becomes critical to comparing their rates of changes over time.

In [118]:
```
we_ta.columns.set_names(['Country Name'], inplace=True)
we_ta.index.set_names(['Year'], inplace=True)

# this is to replace column and index labels with more appropriate titles that matches with WB data

ta_final = we_ta[['France', 'Germany', 'Greece', 'Ireland', 'Spain', 'United Kingdom']]

# here I am narrowing down the countries to just these six countries that I will look at

ta_final
```

Out[118]:

Country Name	France	Germany	Greece	Ireland	Spain	United Kingdom
Year						
2005	33.0	3.0	6.0	0.0	24.0	25.0
2006	34.0	4.0	23.0	1.0	23.0	6.0
2007	16.0	3.0	15.0	1.0	11.0	20.0
2008	13.0	3.0	53.0	5.0	37.0	39.0
2009	9.0	4.0	115.0	0.0	21.0	22.0
2010	3.0	1.0	49.0	4.0	3.0	57.0
2011	8.0	8.0	11.0	4.0	0.0	47.0
2012	65.0	4.0	22.0	29.0	1.0	54.0
2013	12.0	0.0	53.0	27.0	5.0	137.0
2014	14.0	13.0	26.0	33.0	4.0	103.0
2015	36.0	64.0	31.0	28.0	1.0	114.0
2016	26.0	41.0	31.0	15.0	3.0	104.0

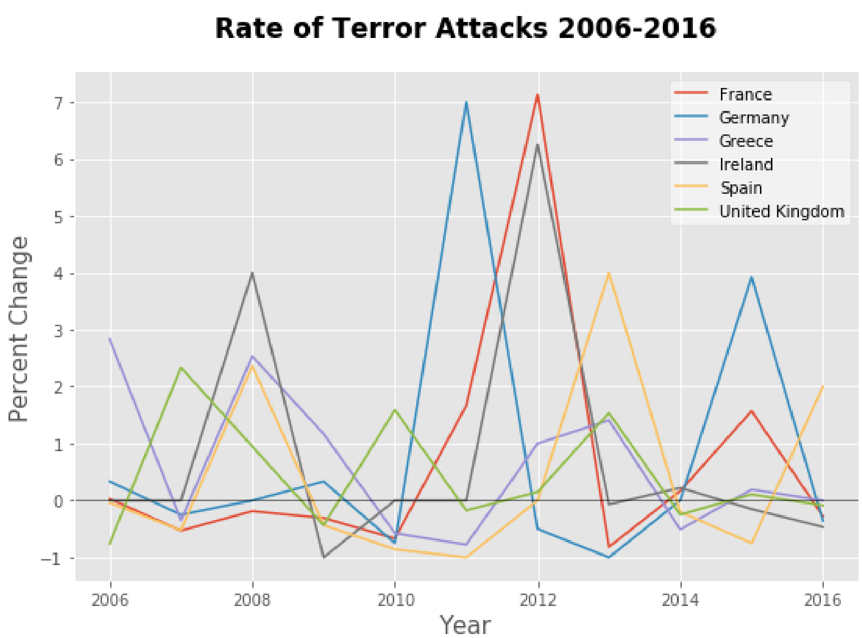
In [119]:
```
ta_rate = ta_final.pct_change(periods=1)
ta_rate.replace(np.inf, 0, inplace=True)

# I want to find the percent change of terrorist attacks for each country after every year
# all values that come out as NaN and inf will be replaced by 0

ta_rate
```

Out[119]:

Country Name	France	Germany	Greece	Ireland	Spain	United Kingdom
Year						
2005	NaN	NaN	NaN	NaN	NaN	NaN
2006	0.030303	0.333333	2.833333	0.000000	-0.041667	-0.760000
2007	-0.529412	-0.250000	-0.347826	0.000000	-0.521739	2.333333
2008	-0.187500	0.000000	2.533333	4.000000	2.363636	0.950000
2009	-0.307692	0.333333	1.169811	-1.000000	-0.432432	-0.435897
2010	-0.666667	-0.750000	-0.573913	0.000000	-0.857143	1.590909
2011	1.666667	7.000000	-0.775510	0.000000	-1.000000	-0.175439
2012	7.125000	-0.500000	1.000000	6.250000	0.000000	0.148936
2013	-0.815385	-1.000000	1.409091	-0.068966	4.000000	1.537037
2014	0.166667	0.000000	-0.509434	0.222222	-0.200000	-0.248175
2015	1.571429	3.923077	0.192308	-0.151515	-0.750000	0.106796
2016	-0.277778	-0.359375	0.000000	-0.464286	2.000000	-0.087719

In [160]:
```
ta_plot = ta_rate.plot(
    figsize = (9,6)
)

# plotting terror attack rates of change on a line graph

ta_plot.spines['right'].set_visible(False)
ta_plot.spines['top'].set_visible(False)
ta_plot.spines['bottom'].set_visible(False)

# I prefer graphs with no spines on top, right, and when there are negative y values, to have the bottom
 spine off as well.

ta_plot.axhline(y=0, color='black', linewidth=0.5)

# I also prefer the graph to include a horizontal line to indicate y=0

ta_plot.set_title('Rate of Terror Attacks 2006-2016', fontsize=17, fontweight='bold', y=1.05)

ta_plot.set_xlabel('Year', fontsize=15)
ta_plot.set_ylabel('Percent Change', fontsize=15)

ta_plot.legend(framealpha=0.5, facecolor='white')

# I prefer the legend to be translucent to the background
```

Out[160]: <matplotlib.legend.Legend at 0x26f14e904a8>



Finding the percentage rate is important to finding how terrorism has increased or decreased for each country. From this graph, it seems that France, Germany, and Ireland have seen dramatic increases between 2010 to 2012. However from just this graph there are no valid conclusions or trends to be made. Whether Western Europe has experienced a noticeable rise in terrorism during a particular period time cannot be determined. Each country seems to have their own moments of increased terrorist activity that is independent from other countries.

Tourism Data: Cleaning and Finding Rates of Change

Data on tourism is grabbed from the World Bank. I am grabbing data from the six same countries specifically from the database that provides statistical information on international arrivals.

In [121]:
```
data_date = (datetime.datetime(2005, 1, 1), datetime.datetime(2016, 1, 1))
tourist = wbdata.get_dataframe({'ST.INT.ARVL':'values'},country=("GBR", "FRA", "ESP", "IRL", "DEU", "GRC"
), data_date=data_date)

# tourism data is grabbed from the World Bank Database, and information on the aforementioned six countri
es will be examined

tourist.head(10)
```

Out[121]:

		values
country	date	
Germany	2016	35555000.0
	2015	34970000.0
	2014	32999000.0
	2013	31545000.0
	2012	30411000.0
	2011	28374000.0
	2010	26875000.0
	2009	24220000.0
	2008	24884000.0
	2007	24421000.0

In [122]:
```
tourist_final = tourist.unstack().T

tourist_final.reset_index(drop=True, level=0, inplace=True)

tourist_final.columns.set_names(['Country Name'], inplace=True)

tourist_final.index.set_names(['Year'], inplace =True)

# these steps will organize the data; the values column on top is dropped and the indenx and column label
s are slightly changed.

tourist_final
```

Out[122]:

Country Name	France	Germany	Greece	Ireland	Spain	United Kingdom
Year						
2005	74988000.0	21500000.0	14765000.0	7333000.0	55914000.0	28039000.0
2006	77916000.0	23569000.0	16039000.0	8001000.0	58004000.0	30654000.0
2007	80853000.0	24421000.0	16165000.0	8332000.0	58666000.0	30870000.0
2008	79218000.0	24884000.0	15939000.0	8026000.0	57192000.0	30142000.0
2009	76764000.0	24220000.0	14915000.0	7189000.0	52178000.0	28199000.0
2010	76647000.0	26875000.0	15007000.0	7134000.0	52677000.0	28295000.0
2011	80499000.0	28374000.0	16427000.0	7630000.0	56177000.0	29306000.0
2012	81980000.0	30411000.0	15518000.0	7550000.0	57464000.0	29282000.0
2013	83634000.0	31545000.0	17920000.0	8260000.0	60675000.0	31063000.0
2014	83701000.0	32999000.0	22033000.0	8813000.0	64939000.0	32613000.0
2015	84452000.0	34970000.0	23599000.0	9528000.0	68175000.0	34436000.0
2016	82570000.0	35555000.0	24799000.0	10100000.0	75315000.0	35814000.0

In [123]:
```
tourist_rate = tourist_final.pct_change(periods=1)

# I also want to find the percentage change for tourism; index type is changed to integer

tourist_rate
```

Out[123]:

Country Name	France	Germany	Greece	Ireland	Spain	United Kingdom
Year						
2005	NaN	NaN	NaN	NaN	NaN	NaN
2006	0.039046	0.096233	0.086285	0.091095	0.037379	0.093263
2007	0.037694	0.036149	0.007856	0.041370	0.011413	0.007046
2008	-0.020222	0.018959	-0.013981	-0.036726	-0.025125	-0.023583
2009	-0.030978	-0.026684	-0.064245	-0.104286	-0.087670	-0.064462
2010	-0.001524	0.109620	0.006168	-0.007651	0.009563	0.003404
2011	0.050256	0.055777	0.094623	0.069526	0.066443	0.035731
2012	0.018398	0.071791	-0.055336	-0.010485	0.022910	-0.000819
2013	0.020176	0.037289	0.154788	0.094040	0.055878	0.060822
2014	0.000801	0.046093	0.229520	0.066949	0.070276	0.049899
2015	0.008972	0.059729	0.071075	0.081130	0.049831	0.055898
2016	-0.022285	0.016729	0.050850	0.060034	0.104730	0.040016

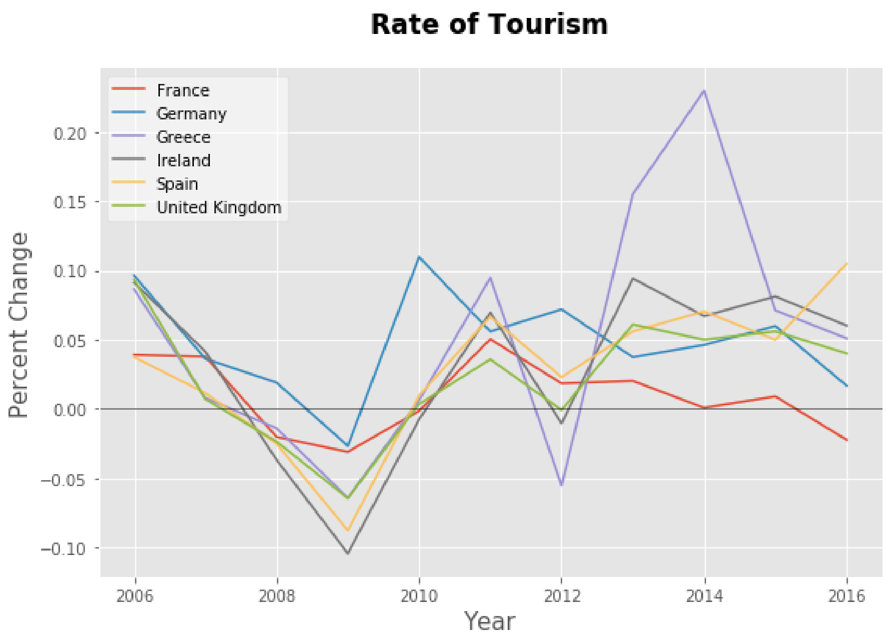
In [124]:
```
tourist_rate.T
```

Out[124]:

Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Country Name											
France	NaN	0.039046	0.037694	-0.020222	-0.030978	-0.001524	0.050256	0.018398	0.020176	0.000801	0.008972
Germany	NaN	0.096233	0.036149	0.018959	-0.026684	0.109620	0.055777	0.071791	0.037289	0.046093	0.059729
Greece	NaN	0.086285	0.007856	-0.013981	-0.064245	0.006168	0.094623	-0.055336	0.154788	0.229520	0.071075
Ireland	NaN	0.091095	0.041370	-0.036726	-0.104286	-0.007651	0.069526	-0.010485	0.094040	0.066949	0.081130
Spain	NaN	0.037379	0.011413	-0.025125	-0.087670	0.009563	0.066443	0.022910	0.055878	0.070276	0.049831
United Kingdom	NaN	0.093263	0.007046	-0.023583	-0.064462	0.003404	0.035731	-0.000819	0.060822	0.049899	0.055898

In [161]:
```
tourist_plot = tourist_rate.plot(
                figsize= (9,6)
                )
# Line graph for tourism rates of change

#instructions are similar to previous graph

tourist_plot.spines['right'].set_visible(False)
tourist_plot.spines['top'].set_visible(False)
tourist_plot.spines['bottom'].set_visible(False)

tourist_plot.axhline(y=0, color='black', linewidth=0.5)

tourist_plot.xaxis.set_ticks_position('bottom')

tourist_plot.set_title('Rate of Tourism', fontsize=17, fontweight='bold', y=1.05)

tourist_plot.set_xlabel('Year', fontsize=15)
tourist_plot.set_ylabel('Percent Change', fontsize=15)

tourist_plot.legend(framealpha=0.5, facecolor='white')
```

Out[161]: <matplotlib.legend.Legend at 0x26f14e689e8>



Similar to the previous graph above, the line plot focuses on the percentage change for rates of tourism. There are some general trends observed in this graph; all countries have experienced a dramatic decrease in tourism around 2008, and a slight drop in 2011. Nothing can be concluded for certain, but there is a more noticeable pattern for rates in tourism than terrorism.

Combining the Data

Terrorism and tourism percentage change data will be concantenated. This final dataframe will be used for most of the data analysis. Several graphs will be created to visualize at once relationship and regression.

In [126]:
```
tourist_rate.index = tourist_rate.index.astype(int)

ta_rate.index = ta_rate.index.astype(int)

# index for both datasets are changed to integer for concatenation
```

In [127]:
```
type(tourist_rate.index)
```

Out[127]: pandas.core.indexes.numeric.Int64Index

In [128]:
```
type(ta_rate.index)
```

Out[128]: pandas.core.indexes.numeric.Int64Index

In [129]:
```
pct_rate = pd.concat([ta_rate, tourist_rate], keys=['tourist_rate', 'attack_rate'], axis=1).fillna(value=
0)

# data of on rates of change for terrorism and tourism is concatenated, columns labels on level=0 are add
ed

pct_rate
```

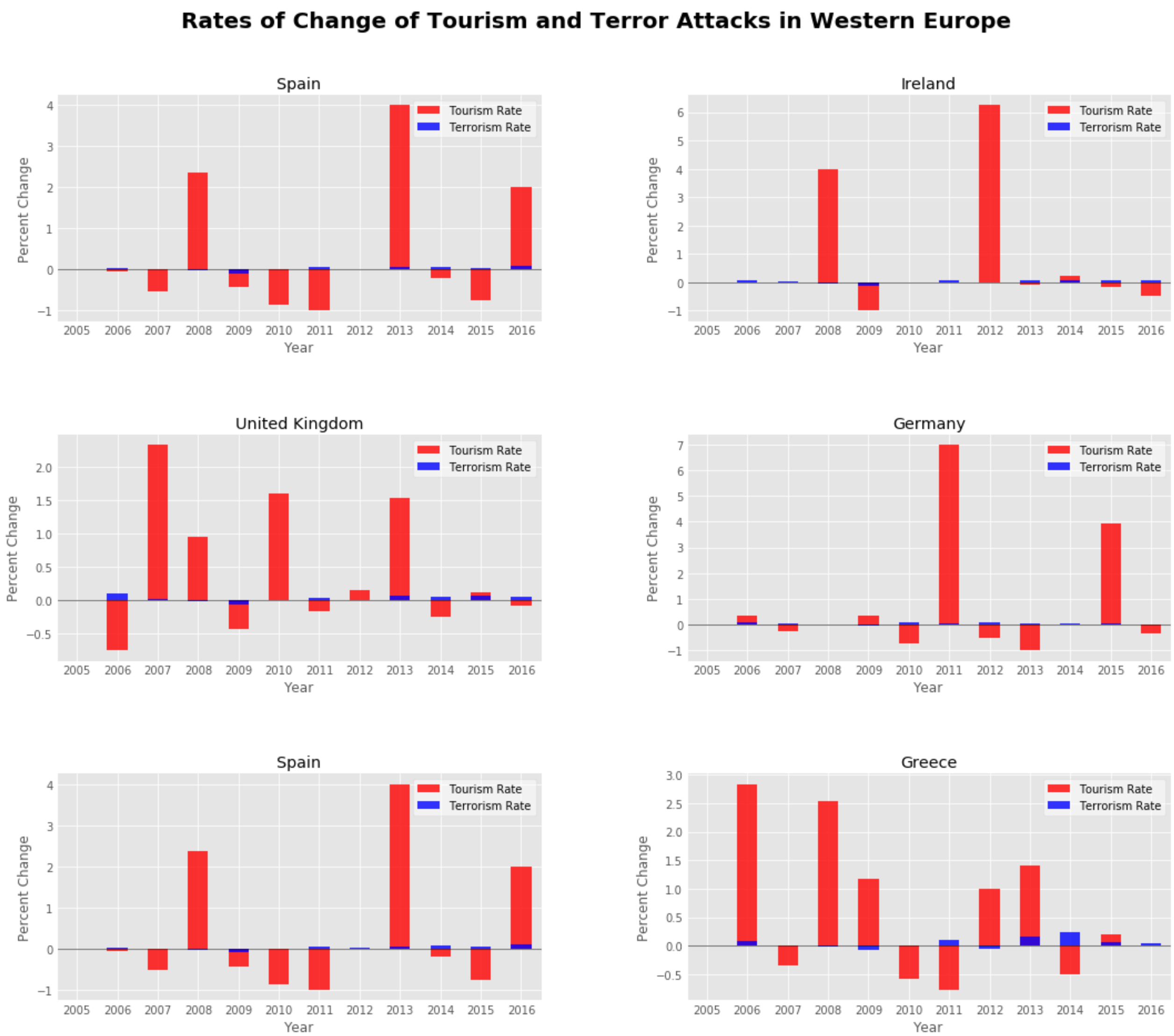
Out[129]:

	tourist_rate						attack_rate				
Country Name	France	Germany	Greece	Ireland	Spain	United Kingdom	France	Germany	Greece	Ireland	Sp
Year											
2005	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0
2006	0.030303	0.333333	2.833333	0.000000	-0.041667	-0.760000	0.039046	0.096233	0.086285	0.091095	0.0
2007	-0.529412	-0.250000	-0.347826	0.000000	-0.521739	2.333333	0.037694	0.036149	0.007856	0.041370	0.0
2008	-0.187500	0.000000	2.533333	4.000000	2.363636	0.950000	-0.020222	0.018959	-0.013981	-0.036726	-0.
2009	-0.307692	0.333333	1.169811	-1.000000	-0.432432	-0.435897	-0.030978	-0.026684	-0.064245	-0.104286	-0.
2010	-0.666667	-0.750000	-0.573913	0.000000	-0.857143	1.590909	-0.001524	0.109620	0.006168	-0.007651	0.0
2011	1.666667	7.000000	-0.775510	0.000000	-1.000000	-0.175439	0.050256	0.055777	0.094623	0.069526	0.0
2012	7.125000	-0.500000	1.000000	6.250000	0.000000	0.148936	0.018398	0.071791	-0.055336	-0.010485	0.0
2013	-0.815385	-1.000000	1.409091	-0.068966	4.000000	1.537037	0.020176	0.037289	0.154788	0.094040	0.0
2014	0.166667	0.000000	-0.509434	0.222222	-0.200000	-0.248175	0.000801	0.046093	0.229520	0.066949	0.0
2015	1.571429	3.923077	0.192308	-0.151515	-0.750000	0.106796	0.008972	0.059729	0.071075	0.081130	0.0
2016	-0.277778	-0.359375	0.000000	-0.464286	2.000000	-0.087719	-0.022285	0.016729	0.050850	0.060034	0.1

This graph provides the complete data on rates of change for both tourism and terrorism from 2005 to 2016. This dataframe will be used to provide further graphic visualization side by side as well as a regression model.

In [163]:
```
fig, ax = plt.subplots(nrows = 3, ncols = 2, figsize=(18,15))
fig.subplots_adjust(hspace=0.5, wspace=0.3)
fig.suptitle('Rates of Change of Tourism and Terror Attacks in Western Europe', fontsize=20, y=.95, fo
ntweight = 'bold')

# 6 stacked bar charts are created for each country to express percentage rates in relation to the tou
rism and terrorism variables

pct_rate['tourist_rate', 'Spain'].plot(kind='bar', color='red', ax=ax[0,0], alpha=0.8, label='Tourism
 Rate')
pct_rate['attack_rate', 'Spain'].plot(kind='bar', color='blue', ax=ax[0,0], alpha=0.8, label='Terroris
m Rate')
ax[0,0].set_title('Spain')
ax[0,0].set_ylabel('Percent Change')
ax[0,0].set_xlabel('Year')
ax[0,0].spines['right'].set_visible(False)
ax[0,0].spines['top'].set_visible(False)
ax[0,0].spines['bottom'].set_visible(False)
ax[0,0].axhline(y=0, color='black', linewidth=0.5)
ax[0,0].legend(framealpha=0.5, facecolor='white')
ax[0,0].tick_params(axis='both', which='both',length=0, rotation='default')

# ticks are off for both axis
# y=0 line is apparent


pct_rate['tourist_rate', 'United Kingdom'].plot(kind='bar', color='red', ax=ax[1,0], alpha=0.8, label=
'Tourism Rate')
pct_rate['attack_rate', 'United Kingdom'].plot(kind='bar', color='blue', ax=ax[1,0], alpha=0.8, label=
'Terrorism Rate')
ax[1,0].set_title('United Kingdom')
ax[1,0].set_ylabel('Percent Change')
ax[1,0].set_xlabel('Year')
ax[1,0].spines['right'].set_visible(False)
ax[1,0].spines['top'].set_visible(False)
ax[1,0].spines['bottom'].set_visible(False)
ax[1,0].axhline(y=0, color='black', linewidth=0.5)
ax[1,0].legend(framealpha=0.5, facecolor='white')
ax[1,0].tick_params(axis='both', which='both',length=0, rotation='default')

pct_rate['tourist_rate', 'Germany'].plot(kind='bar', color='red', ax=ax[1,1], alpha=0.8, label='Touris
m Rate')
pct_rate['attack_rate', 'Germany'].plot(kind='bar', color='blue', ax=ax[1,1], alpha=0.8, label='Terror
ism Rate')
ax[1,1].set_title('Germany')
ax[1,1].set_ylabel('Percent Change')
ax[1,1].set_xlabel('Year')
ax[1,1].spines['right'].set_visible(False)
ax[1,1].spines['top'].set_visible(False)
ax[1,1].spines['bottom'].set_visible(False)
ax[1,1].axhline(y=0, color='black', linewidth=0.5)
ax[1,1].legend(framealpha=0.5, facecolor='white')
ax[1,1].tick_params(axis='both', which='both',length=0, rotation='default')

pct_rate['tourist_rate', 'Ireland'].plot(kind='bar', color='red', ax=ax[0,1], alpha=0.8, label='Touris
m Rate')
pct_rate['attack_rate', 'Ireland'].plot(kind='bar', color='blue', ax=ax[0,1], alpha=0.8, label='Terror
ism Rate')
ax[0,1].set_title('Ireland')
ax[0,1].set_ylabel('Percent Change')
ax[0,1].set_xlabel('Year')
ax[0,1].spines['right'].set_visible(False)
ax[0,1].spines['top'].set_visible(False)
ax[0,1].spines['bottom'].set_visible(False)
ax[0,1].axhline(y=0, color='black', linewidth=0.5)
ax[0,1].legend(framealpha=0.5, facecolor='white')
ax[0,1].tick_params(axis='both', which='both',length=0, rotation='default')

pct_rate['tourist_rate', 'Spain'].plot(kind='bar', color='red', ax=ax[2,0], alpha=0.8, label='Tourism
 Rate')
pct_rate['attack_rate', 'Spain'].plot(kind='bar', color='blue', ax=ax[2,0], alpha=0.8, label='Terroris
m Rate')
ax[2,0].set_title('Spain')
```

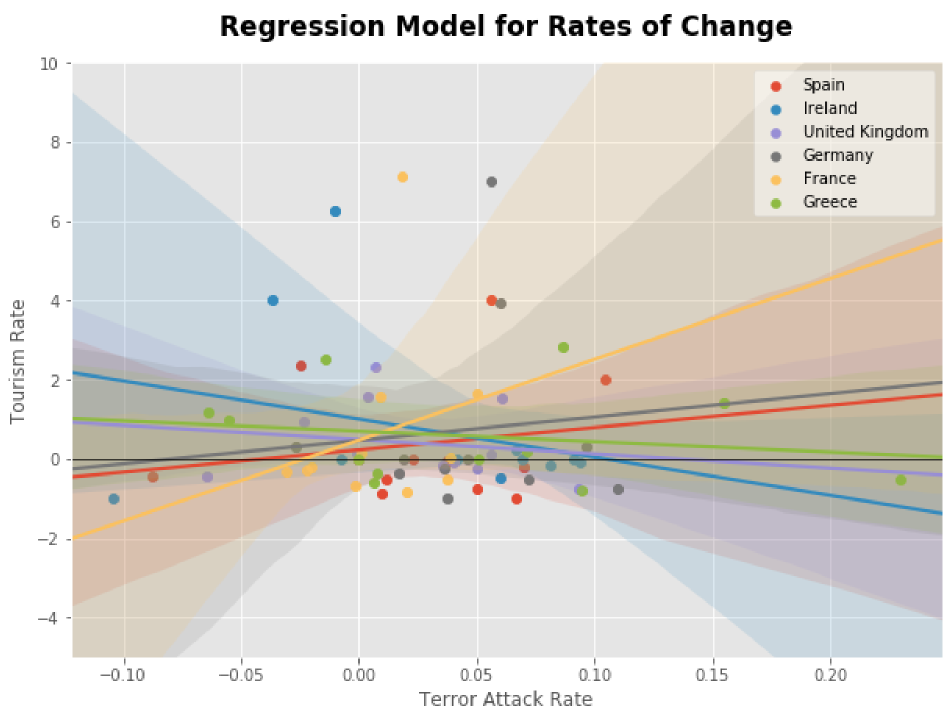
```
ax[2,0].set_ylabel('Percent Change')
ax[2,0].set_xlabel('Year')
ax[2,0].spines['right'].set_visible(False)
ax[2,0].spines['top'].set_visible(False)
ax[2,0].spines['bottom'].set_visible(False)
ax[2,0].axhline(y=0, color='black', linewidth=0.5)
ax[2,0].legend(framealpha=0.5, facecolor='white')
ax[2,0].tick_params(axis='both', which='both',length=0, rotation='default')

pct_rate['tourist_rate', 'Greece'].plot(kind='bar', color='red', ax=ax[2,1], alpha=0.8, label='Tourism
 Rate')
pct_rate['attack_rate', 'Greece'].plot(kind='bar', color='blue', ax=ax[2,1], alpha=0.8, label='Terrori
sm Rate')
ax[2,1].set_title('Greece')
ax[2,1].set_ylabel('Percent Change')
ax[2,1].set_xlabel('Year')
ax[2,1].spines['right'].set_visible(False)
ax[2,1].spines['top'].set_visible(False)
ax[2,1].spines['bottom'].set_visible(False)
ax[2,1].axhline(y=0, color='black', linewidth=0.5)
ax[2,1].legend(framealpha=0.5, facecolor='white')
ax[2,1].tick_params(axis='both', which='both',length=0, rotation='default')
```



Here, a 3 by 2 figure with subplots is congregated by stack bar charts for percentage rates of each country. Again there does not seem to be any noticeable patterns just from observation. However it is obvious that tourism rates experience greater fluxuation than terrorism rates in all countries. It is normal to tourism to see a 2 or greater percent in change, but but terrorism rates often see less than 0.5 percent in change.

In [166]:
```
fig, ax = plt.subplots(figsize=(10,7))

ax.set_title('Regression Model for Rates of Change', fontsize=17, y=1.03, fontweight='bold')

# regression scatter plot for rate of change of each country

ax.set_ylim(-5,10)
ax.set_xlabel('Attack Rate')
ax.set_ylabel('Tourist Rate')

ax.scatter(y=pct_rate.tourist_rate.Spain, x=pct_rate.attack_rate.Spain)
ax.scatter(y=pct_rate.tourist_rate.Ireland, x=pct_rate.attack_rate.Ireland)
ax.scatter(y=pct_rate.tourist_rate['United Kingdom'], x=pct_rate.attack_rate['United Kingdom'])
ax.scatter(y=pct_rate.tourist_rate.Germany, x=pct_rate.attack_rate.Germany)
ax.scatter(y=pct_rate.tourist_rate.France, x=pct_rate.attack_rate.France)
ax.scatter(y=pct_rate.tourist_rate.Greece, x=pct_rate.attack_rate.Greece)

sns.regplot(y=pct_rate.tourist_rate.Spain, x=pct_rate.attack_rate.Spain)
sns.regplot(y=pct_rate.tourist_rate.Ireland, x=pct_rate.attack_rate.Ireland)
sns.regplot(y=pct_rate.tourist_rate['United Kingdom'], x=pct_rate.attack_rate['United Kingdom'])
sns.regplot(y=pct_rate.tourist_rate.Germany, x=pct_rate.attack_rate.Germany)
sns.regplot(y=pct_rate.tourist_rate.France, x=pct_rate.attack_rate.France)
sns.regplot(y=pct_rate.tourist_rate.Greece, x=pct_rate.attack_rate.Greece)

ax.axhline(y=0, color='black', linewidth=0.7)

ax.set(xlabel='Terror Attack Rate', ylabel='Tourism Rate')

ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
ax.spines['bottom'].set_visible(False)

ax.legend(framealpha=0.5, facecolor='white')
```

Out[166]: <matplotlib.legend.Legend at 0x26f16757a20>



This regression graph shows the relationship between terror attack rate and tourism rate, and if possibly there is a relationship between these two variables. Just from observation, there seems to be no relationship between the independent and dependent variable that are consistent with all the countries. France has the strongest positive relationship, while Ireland has the strongest negative relationship. The rest of the countries have slight positive and negative relationships. The verdict is evenly split on whether there is a definitive positive/negative relationship overall.

Below are summaries of each countries' regression results:

Ireland

In [138]:
```
x = pct_rate.attack_rate.Ireland # x will be the independent variable, or rate of terrorist activity
y = pct_rate.tourist_rate.Ireland # y will be the dependent variable or rate of tourism
x = sm.add_constant(X) # an x-intercept will be added

model = sm.OLS(y,x).fit()
## sm.OLS(output, input)

predictions = model.predict(x)

model.summary()
```

```
C:\Users\Shirley Liao\Anaconda3\Anaconda Python\lib\site-packages\scipy\stats\stats.py:1390: UserWarnin
g: kurtosistest only valid for n>=20 ... continuing anyway, n=12
  "anyway, n=%i" % int(n))
```

Out[138]:

OLS Regression Results

Dep. Variable:	Ireland	**R-squared:**	0.015
Model:	OLS	**Adj. R-squared:**	-0.083
Method:	Least Squares	**F-statistic:**	0.1526
Date:	Mon, 14 May 2018	**Prob (F-statistic):**	0.704
Time:	22:33:21	**Log-Likelihood:**	-25.489
No. Observations:	12	**AIC:**	54.98
Df Residuals:	10	**BIC:**	55.95
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.8683	0.729	1.192	0.261	-0.755	2.492
Spain	-5.1693	13.231	-0.391	0.704	-34.650	24.312

Omnibus:	14.096	**Durbin-Watson:**	2.435
Prob(Omnibus):	0.001	**Jarque-Bera (JB):**	8.573
Skew:	1.783	**Prob(JB):**	0.0138
Kurtosis:	5.103	**Cond. No.**	20.7

France

In [139]:

```
x = pct_rate.attack_rate.France
y = pct_rate.tourist_rate.France
x = sm.add_constant(X)

model = sm.OLS(y, x).fit()
predictions = model.predict(x)

model.summary()
```

```
C:\Users\Shirley Liao\Anaconda3\Anaconda Python\lib\site-packages\scipy\stats\stats.py:1390: UserWarnin
g: kurtosistest only valid for n>=20 ... continuing anyway, n=12
  "anyway, n=%i" % int(n))
```

Out[139]:

OLS Regression Results

Dep. Variable:	France	**R-squared:**	0.007
Model:	OLS	**Adj. R-squared:**	-0.092
Method:	Least Squares	**F-statistic:**	0.07550
Date:	Mon, 14 May 2018	**Prob (F-statistic):**	0.789
Time:	22:33:24	**Log-Likelihood:**	-25.849
No. Observations:	12	**AIC:**	55.70
Df Residuals:	10	**BIC:**	56.67
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.5494	0.751	0.732	0.481	-1.123	2.222
Spain	3.7462	13.634	0.275	0.789	-26.631	34.124

Omnibus:	25.109	**Durbin-Watson:**	2.095
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	23.657
Skew:	2.428	**Prob(JB):**	7.29e-06
Kurtosis:	7.872	**Cond. No.**	20.7

Germany

In [140]:
```
x = pct_rate.attack_rate.Germany
y = pct_rate.tourist_rate.Germany
x = sm.add_constant(X)

model = sm.OLS(y, x).fit()
predictions = model.predict(x)

model.summary()
```

```
C:\Users\Shirley Liao\Anaconda3\Anaconda Python\lib\site-packages\scipy\stats\stats.py:1390: UserWarnin
g: kurtosistest only valid for n>=20 ... continuing anyway, n=12
  "anyway, n=%i" % int(n))
```

Out[140]:

OLS Regression Results

Dep. Variable:	Germany	**R-squared:**	0.053
Model:	OLS	**Adj. R-squared:**	-0.042
Method:	Least Squares	**F-statistic:**	0.5584
Date:	Mon, 14 May 2018	**Prob (F-statistic):**	0.472
Time:	22:33:26	**Log-Likelihood:**	-26.384
No. Observations:	12	**AIC:**	56.77
Df Residuals:	10	**BIC:**	57.74
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.4473	0.785	0.570	0.581	-1.302	2.196
Spain	10.6528	14.256	0.747	0.472	-21.111	42.416

Omnibus:	12.061	**Durbin-Watson:**	2.607
Prob(Omnibus):	0.002	**Jarque-Bera (JB):**	6.837
Skew:	1.637	**Prob(JB):**	0.0328
Kurtosis:	4.719	**Cond. No.**	20.7

United Kingdom

In [101]:
```
x = pct_rate.attack_rate['United Kingdom']
y = pct_rate.tourist_rate['United Kingdom']
x = sm.add_constant(X)


model = sm.OLS(y, x).fit()
predictions = model.predict(x)

model.summary()
```

```
C:\Users\Shirley Liao\Anaconda3\Anaconda Python\lib\site-packages\scipy\stats\stats.py:1390: UserWarnin
g: kurtosistest only valid for n>=20 ... continuing anyway, n=12
  "anyway, n=%i" % int(n))
```

Out[101]:

OLS Regression Results

Dep. Variable:	United Kingdom	**R-squared:**	0.008
Model:	OLS	**Adj. R-squared:**	-0.092
Method:	Least Squares	**F-statistic:**	0.07632
Date:	Mon, 14 May 2018	**Prob (F-statistic):**	0.788
Time:	22:18:53	**Log-Likelihood:**	-15.942
No. Observations:	12	**AIC:**	35.88
Df Residuals:	10	**BIC:**	36.85
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.4567	0.329	1.389	0.195	-0.276	1.189
Spain	-1.6497	5.971	-0.276	0.788	-14.955	11.656

Omnibus:	1.888	**Durbin-Watson:**	2.700
Prob(Omnibus):	0.389	**Jarque-Bera (JB):**	1.319
Skew:	0.748	**Prob(JB):**	0.517
Kurtosis:	2.368	**Cond. No.**	20.7

Greece

In [102]:
```
x = pct_rate.attack_rate.Greece
y = pct_rate.tourist_rate.Greece
x = sm.add_constant(X)

model = sm.OLS(y, x).fit()
predictions = model.predict(x)

model.summary()
```

```
C:\Users\Shirley Liao\Anaconda3\Anaconda Python\lib\site-packages\scipy\stats\stats.py:1390: UserWarnin
g: kurtosistest only valid for n>=20 ... continuing anyway, n=12
  "anyway, n=%i" % int(n))
```

Out[102]:

OLS Regression Results

Dep. Variable:	Greece	**R-squared:**	0.115
Model:	OLS	**Adj. R-squared:**	0.026
Method:	Least Squares	**F-statistic:**	1.297
Date:	Mon, 14 May 2018	**Prob (F-statistic):**	0.281
Time:	22:19:17	**Log-Likelihood:**	-18.076
No. Observations:	12	**AIC:**	40.15
Df Residuals:	10	**BIC:**	41.12
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.7913	0.393	2.014	0.072	-0.084	1.666
Spain	-8.1236	7.133	-1.139	0.281	-24.017	7.770

Omnibus:	2.201	**Durbin-Watson:**	2.700
Prob(Omnibus):	0.333	**Jarque-Bera (JB):**	1.407
Skew:	0.804	**Prob(JB):**	0.495
Kurtosis:	2.524	**Cond. No.**	20.7

Spain

In [103]:
```
x = pct_rate.attack_rate.Spain
y = pct_rate.tourist_rate.Spain
x = sm.add_constant(X)

model = sm.OLS(y, x).fit()
predictions = model.predict(x)

model.summary()
```

```
C:\Users\Shirley Liao\Anaconda3\Anaconda Python\lib\site-packages\scipy\stats\stats.py:1390: UserWarnin
g: kurtosistest only valid for n>=20 ... continuing anyway, n=12
  "anyway, n=%i" % int(n))
```

Out[103]:

OLS Regression Results

Dep. Variable:	Spain	**R-squared:**	0.033
Model:	OLS	**Adj. R-squared:**	-0.063
Method:	Least Squares	**F-statistic:**	0.3448
Date:	Mon, 14 May 2018	**Prob (F-statistic):**	0.570
Time:	22:19:48	**Log-Likelihood:**	-21.612
No. Observations:	12	**AIC:**	47.22
Df Residuals:	10	**BIC:**	48.19
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.2321	0.527	0.440	0.669	-0.943	1.407
Spain	5.6241	9.577	0.587	0.570	-15.716	26.964

Omnibus:	5.721	**Durbin-Watson:**	2.229
Prob(Omnibus):	0.057	**Jarque-Bera (JB):**	2.969
Skew:	1.209	**Prob(JB):**	0.227
Kurtosis:	3.304	**Cond. No.**	20.7

Conclusion (Final Thoughts)

This goal of this project is to manipulate, analyze, and visualize the data on terrorism and tourism. At the core of the project, I wanted to know if general assumptions on terrorism and tourism based on media was true.

Were there actually more terrorist activity in Western Europe in recent years than in the past few decades? Looking at general counts from each country, this is mixed. The UK, Ireland, and Germany there has seen a consistent increase. However for Greece and France there have been periods on fluxuation, and for Spain it has even seen a drop. What I looked at were their rates of change, which more importantly considers how rapidly terrorist activity have risen or declined in the last 12 years. Upon observing percentage changes, this provides even less of a clear trend. This is because there are generally small incremental changes each year, which in a small time span, does not really provide strong conclusions.

Is tourism even affected by terrorism, and can we trust the data? In completing the project, I've noticed how influential large quantities are in observing change. Obviously (and thankfully), tourism data works with greater numbers, and as a result, countries experience more dramatic rates of change per year. But there are also really mixed results, with some countries experiencing dramatic increases and decreases in some years, while in others, sees almost no change in the amount of tourists. Other factors can also be at play for these change, and they can't be discounted. Recessions, politics, and other trends in tourism needs to be factored in also. Overall tourism in Western Europe is quite consistent if you look at quantity, but rates of change are more striking. The region on its own is a hotspot for tourism.

There is no conclusive result on whether terrorism affects tourism. More in-depth research is necessary to find if there is a definitive relationship. Nonetheless it is satisfying enough in preparing this data to see how each country has change over time through these variables.