Data Bootcamp Final Project Fall 2017

The Impact of Terrorism Political Stability

Author: Rayan Elsharkawi

Email: rayan@nyu.edu

Introduction

Considering current events, terrorist attacks have increased globally. I am interested in exploring the impact of terrorist attacks on political stability, or instability. This will reveal how small or big of an impact terrorism has on each country's stability. After descriptively exploring and analyzing the data, I will use basic regression methods to observe the statistical relationship between terrorism and political stability. I predict that increased terrorist activity is strongly tied to increased political instability.

Data and Variables

Obtaining data on terrorism is very difficult due to its scarcity. On the rise currently are metrics such as the Global Terrorism Index (GTI), an an all-encompassing metric based on four factors: the number of terrorist incidents per year, the number of fatalities caused by terrorists per year, the number of injuries caused by terrorists per year, and total property damage caused by terrorism per year. The problem with such metrics is that the data only exists, at least publicly and for free, for a very small number of observations for a specific year. Certainly, this is quite restricting. As a result, I have chosen to create my own aggregate variables from a dataset available on Kaggle called "Global Terrorism Database," provided by the University of Maryland. The data set is not available on the University of Maryland's website to the public; one must request special permission to be granted access to it.

Here is the link to the Kaggle dataset: https://www.kaggle.com/ash316/terrorism-around-the-world/data (https://www.kaggle.com/ash316/terrorism-around-the-world/data)

Here is the link to the University of Maryland's Terrorism Research website: https://www.start.umd.edu/gtd/ (https://www.start.umd.edu/gtd/)

From this data set, I will construct a terrorism casualities metric, by aggregating data on the number of fatalities caused by terrorism per country, and data on the number of injuries caused by terrorism per country, both of which exist for many years and many countries. Some of the goals of this project are to observe cross-country differences as well as trends over time. However, because this dataset is extremely large, I have removed all the data and variables of the years that I will not be analyzing in order to augment the speed of execution and to be able to post such an abbreviated dataset on Github.

The second variable that I will observe is the Political Stability Index (PSI) measures The PSI ranges from -2.5 to 2.5, with -2.5 being extremely politically unstable, and 2.5 being extremely politically stable. The PSI data is obtained from: http://info.worldbank.org/governance/wgi/#home (http://info.worldbank.org/governance/wgi/#home) . This is a historical data set of the PSI of all countries over time. It includes, PSI estimates, PSI standard error, PSI ranges, etc. For the purpose of this project, I will use the PSI estimates. Once again, while offline, I downloaded and cleaned the excel sheet, removing all unwanted data.

Due to the limitations of all of the data sets that I will use, I have decided to focus my research on data from the years 2014 to 2016.

Project Outline

1. Cleaning & Organizing the Datasets
2. Descriptive Analysis: Observing the Top 20 Countries with the Highest Casualities
3. Descriptive Analysis: Terrorism Density Graphs
4. Descriptive Analysis: Political Stability vs. Terrorism Density
5. Statistical Analysis: OLS regression with PSI and Terrorism
6. Concluding Remarks

Installing Packages

Below, I began by installing all the packages that I will be using to visualize and analyze the data.

In [148]:
```
from IPython.display import display, Image
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from mpl_toolkits.basemap import Basemap

import statsmodels.api as sm
import statsmodels.formula.api as smf

import plotly.plotly as py

import geopandas as gpd
from shapely.geometry import Point, Polygon
import fiona
```

Here, I am linking the first data set that I will use, with the terrorism data, which was cleaned offline in order to minimize the file's size. The data will be placed into a dataframe.

In [170]:
```
path = 'C:\\Users\\Rayan\\Documents\\Junior Year\\Fall 2017\\Data Bootcamp\\Final Project\\globalterrorismdbshort.csv'

url1 = "https://github.com/rsharkawy/Data-Bootcamp-Final-Project/blob/master/globalterrorismdbshort.csv"

df = pd.read_csv(url1, low_memory=False, encoding='ISO-8859-1')

type(df)
```

```
---------------------------------------------------------------------------
ParserError                               Traceback (most recent call last)
<ipython-input-170-e15d756c7b57> in <module>()
      3 url1 = "https://github.com/rsharkawy/Data-Bootcamp-Final-Project/bl
ob/master/globalterrorismdbshort.csv"
      4 
----> 5 df = pd.read_csv(url1, low_memory=False, encoding='ISO-8859-1')
      6 
      7 type(df)

C:\Users\Rayan\Anaconda3\lib\site-packages\pandas\io\parsers.py in parser_f
(filepath_or_buffer, sep, delimiter, header, names, index_col, usecols, squ
eeze, prefix, mangle_dupe_cols, dtype, engine, converters, true_values, fal
se_values, skipinitialspace, skiprows, nrows, na_values, keep_default_na, n
a_filter, verbose, skip_blank_lines, parse_dates, infer_datetime_format, ke
ep_date_col, date_parser, dayfirst, iterator, chunksize, compression, thous
ands, decimal, lineterminator, quotechar, quoting, escapechar, comment, enc
oding, dialect, tupleize_cols, error_bad_lines, warn_bad_lines, skipfooter,
 skip_footer, doublequote, delim_whitespace, as_recarray, compact_ints, use
_unsigned, low_memory, buffer_lines, memory_map, float_precision)
    703                     skip_blank_lines=skip_blank_lines)
    704 
--> 705         return _read(filepath_or_buffer, kwds)
    706 
    707     parser_f.__name__ = name

C:\Users\Rayan\Anaconda3\lib\site-packages\pandas\io\parsers.py in _read(fi
lepath_or_buffer, kwds)
    449 
    450     try:
--> 451         data = parser.read(nrows)
    452     finally:
    453         parser.close()

C:\Users\Rayan\Anaconda3\lib\site-packages\pandas\io\parsers.py in read(sel
f, nrows)
   1063                 raise ValueError('skipfooter not supported for iter
ation')
   1064 
-> 1065         ret = self._engine.read(nrows)
   1066 
   1067         if self.options.get('as_recarray'):

C:\Users\Rayan\Anaconda3\lib\site-packages\pandas\io\parsers.py in read(sel
f, nrows)
   1826     def read(self, nrows=None):
   1827         try:
-> 1828             data = self._reader.read(nrows)
   1829         except StopIteration:
   1830             if self._first_chunk:

pandas\_libs\parsers.pyx in pandas._libs.parsers.TextReader.read()

pandas\_libs\parsers.pyx in pandas._libs.parsers.TextReader._read_rows()

pandas\_libs\parsers.pyx in pandas._libs.parsers.raise_parser_error()
```

```
ParserError: Error tokenizing data. C error: Expected 1 fields in line 116,
 saw 3
```

Cleaning the Data

In this section, I am going to continue to organize the data. I commonly create copies of the original dataframe. This is because if I accidentally alter the dataframe, by using the drop command for example, I don't want the consequences to be difficult to reverse. After creating a copy, I observe the size of the dataframe.

In [171]:
```
df1 = df #created a copy of the dataframe

df.shape #returns (# of rows, # of columns) in the dataset
```

Out[171]:
```
(45201, 14)
```

In [172]:
```
type(df1) #just to check that it is a dataframe indeed
```

Out[172]:
```
pandas.core.frame.DataFrame
```

Below, I am outputting the type of each of the variables (one variable per column), in order to familiarize myself with the data that I am dealing with.

In [173]:
```
df1.dtypes
```

Out[173]:
```
eventid              float64
year                   int64
month                  int64
day                    int64
country               object
region                object
provstate             object
city                  object
latitude             float64
longitude            float64
summary               object
killed               float64
wounded              float64
totalCasualities     float64
dtype: object
```

I am renaming the column names in the dataset to facilitate my interaction with the data and minimize personal errors. After that, I finally create a new variable called totalCasualities, which as the name suggests, is the total number of casualities equivalent to the sum of all the people killed and injured in a terrorist attack.

Note that in this dataframe, each row is a terrorist event. Essentially, what this step is doing is aggregating the casualities for each event.

In [174]:
```
df1.rename(columns={'iyear':'year','imonth':'month','iday':'day','country_txt'
:'country','region_txt':'region','nkill':'killed','nwound':'wounded'},inplace=
True)
```

In [175]:
```
df1["totalCasualities"]=df1["killed"]+df1["wounded"]
df1.head()
```

Out[175]:

	eventid	year	month	day	country	region	provstate	city	latitud
0	2.010000e+11	2014	1	1	Colombia	South America	Norte de Santander	Convencion	8.868790
1	2.010000e+11	2014	1	1	Somalia	Sub-Saharan Africa	Banaadir	Mogadishu	2.038353
2	2.010000e+11	2014	1	1	Pakistan	South Asia	Balochistan	Quetta	30.19133
3	2.010000e+11	2014	1	1	Pakistan	South Asia	Balochistan	Dera Bugti	29.03333
4	2.010000e+11	2014	1	1	Somalia	Sub-Saharan Africa	Middle Juba	Buale	1.097128

In [176]:
```
df1.shape #ensuring that the dataframe is still the same size.
```

Out[176]: (45201, 14)

As previously mentioned, I am observing terrorism trends over the past three years, from 2014 to 2016. Below, I create duplicates of the terrorism dataframe such that each duplicate contains data strictly for one of the respective years.

In [177]:
```
df_2014 = df1[df1.year==2014]
df_2015 = df1[df1.year==2015]
df_2016 = df1[df1.year==2016]
```

I am interested in looking at aggregate casualities by country, rather than by individual event. So, I grouped all the events in each dataframe by country. Once again, I continue making new duplicate dataframes.

In [178]:
```
dfnew2014 = df_2014.groupby("country")
dfnew2015 = df_2015.groupby("country")
dfnew2016 = df_2016.groupby("country")
```

In [179]:
```
dfnew2015.head() #just to check and observe what the above dataframes would lo
ok like
```

Out[179]:

	eventid	year	month	day	country	region	provstate	cit
15820	2.010000e+11	2015	1	3	Iraq	Middle East & North Africa	Baghdad	Baghdad
16508	2.010000e+11	2015	1	1	Bosnia-Herzegovina	Eastern Europe	Federation of Bosnia and Herzegovina	Trnovi
16860	2.020000e+11	2015	1	1	Iraq	Middle East & North Africa	Baghdad	Baghdad
16861	2.020000e+11	2015	1	1	Sweden	Western Europe	Uppsala	Uppsala
16862	2.020000e+11	2015	1	1	Libya	Middle East & North Africa	Benghazi	Benghazi
16863	2.020000e+11	2015	1	1	Iraq	Middle East & North Africa	Baghdad	Baghdad
16864	2.020000e+11	2015	1	1	Iraq	Middle East & North Africa	Baghdad	Baghdad
16865	2.020000e+11	2015	1	1	Iraq	Middle East & North Africa	Baghdad	Baghdad

	eventid	year	month	day	country	region	provstate	cit
16869	2.020000e+11	2015	1	1	Turkey	Middle East & North Africa	Istanbul	Istanbul
16870	2.020000e+11	2015	1	1	India	South Asia	Tamil Nadu	Sivaganga
16871	2.020000e+11	2015	1	1	Afghanistan	South Asia	Kapisa	Kortas
16872	2.020000e+11	2015	1	1	Pakistan	South Asia	Sindh	Karachi
16873	2.020000e+11	2015	1	1	Indonesia	Southeast Asia	Papua	Utikini Baru
16874	2.020000e+11	2015	1	1	Pakistan	South Asia	Balochistan	Sibi
16875	2.020000e+11	2015	1	1	Pakistan	South Asia	Balochistan	Loralai district
16877	2.020000e+11	2015	1	1	Afghanistan	South Asia	Nangarhar	Jalalabad
16878	2.020000e+11	2015	1	1	West Bank and Gaza Strip	Middle East & North Africa	West Bank	Jerusalem

	eventid	year	month	day	country	region	provstate	cit
16879	2.020000e+11	2015	1	1	Ukraine	Eastern Europe	Luhansk	Staryi Aydar
16880	2.020000e+11	2015	1	1	Ukraine	Eastern Europe	Luhansk	Zolote
16881	2.020000e+11	2015	1	1	Ukraine	Eastern Europe	Donetsk	Vuhlehirsk
16882	2.020000e+11	2015	1	1	Ukraine	Eastern Europe	Luhansk	Popasna
16883	2.020000e+11	2015	1	1	Ukraine	Eastern Europe	Donetsk	Chermalyk
16891	2.020000e+11	2015	1	1	Nigeria	Sub-Saharan Africa	Gombe	Gombe
16892	2.020000e+11	2015	1	1	Cameroon	Sub-Saharan Africa	Extreme-North	Unknown
16894	2.020000e+11	2015	1	1	Afghanistan	South Asia	Farah	Barangak
16895	2.020000e+11	2015	1	1	India	South Asia	Chhattisgarh	Kottapalli

	eventid	year	month	day	country	region	provstate	cit
16896	2.020000e+11	2015	1	1	Yemen	Middle East & North Africa	Hadramawt	Shibam
16897	2.020000e+11	2015	1	1	Yemen	Middle East & North Africa	Hadramawt	Shibam
16898	2.020000e+11	2015	1	1	Yemen	Middle East & North Africa	Marib	Unknown
16899	2.020000e+11	2015	1	1	Syria	Middle East & North Africa	Aleppo	Aleppo
...	...	...	...	...	...	...	...	...
29725	2.020000e+11	2015	11	8	Italy	Western Europe	Emilia-Romagna	Bologna
29744	2.020000e+11	2015	11	9	Jordan	Middle East & North Africa	Amman	Muwaqqar
29891	2.020000e+11	2015	11	12	Italy	Western Europe	Lombardy	Milan
29981	2.020000e+11	2015	11	14	Canada	North America	Ontario	Peterboroug
30000	2.020000e+11	2015	11	14	Netherlands	Western Europe	North Brabant	Roosendaal

	eventid	year	month	day	country	region	provstate	cit
30059	2.020000e+11	2015	11	16	Canada	North America	Ontario	Toronto
30113	2.020000e+11	2015	11	18	Bosnia-Herzegovina	Eastern Europe	Federation of Bosnia and Herzegovina	Rajlovac
30188	2.020000e+11	2015	11	19	Kyrgyzstan	Central Asia	Bishkek	Bishkek
30222	2.020000e+11	2015	11	20	Bosnia-Herzegovina	Eastern Europe	Federation of Bosnia and Herzegovina	Salakovac
30226	2.020000e+11	2015	11	20	South Africa	Sub-Saharan Africa	North West	Marikana
30272	2.020000e+11	2015	11	21	Finland	Western Europe	Northern Ostrobothnia	Oulu
30365	2.020000e+11	2015	11	23	Argentina	South America	Ciudad de Buenos Aires	Buenos Aire
30434	2.020000e+11	2015	11	25	Venezuela	South America	Guarico	Altagracia d Orituco
30648	2.020000e+11	2015	12	1	Finland	Western Europe	Satakunta	Kankaanpaa

	eventid	year	month	day	country	region	provstate	cit
30678	2.020000e+11	2015	12	2	Ivory Coast	Sub-Saharan Africa	Bas-Sassandra	Grabo
30679	2.020000e+11	2015	12	2	Ivory Coast	Sub-Saharan Africa	Bas-Sassandra	Grabo
30754	2.020000e+11	2015	12	4	Finland	Western Europe	Satakunta	Rauma
30811	2.020000e+11	2015	12	6	Armenia	Central Asia	Yerevan	Yerevan
30834	2.020000e+11	2015	12	7	Kosovo	Eastern Europe	Pec	Gorazhdec
30961	2.020000e+11	2015	12	11	Ethiopia	Sub-Saharan Africa	Addis Ababa	Addis Ababa
31044	2.020000e+11	2015	12	13	Italy	Western Europe	Lazio	Rome
31118	2.020000e+11	2015	12	15	Ethiopia	Sub-Saharan Africa	Amhara	Metema
31213	2.020000e+11	2015	12	18	Italy	Western Europe	Lombardy	Brescia

	eventid	year	month	day	country	region	provstate	cit
31229	2.020000e+11	2015	12	18	Estonia	Eastern Europe	Harju	Tallinn
31327	2.020000e+11	2015	12	21	Djibouti	Sub-Saharan Africa	Djibouti	Djibouti
31361	2.020000e+11	2015	12	22	Venezuela	South America	Miranda	Caracas
31515	2.020000e+11	2015	12	23	Spain	Western Europe	Madrid	Madrid
31611	2.020000e+11	2015	12	28	Laos	Southeast Asia	Vientiane	Unknown
31676	2.020000e+11	2015	12	30	Laos	Southeast Asia	Vientiane	Namphanoy
31710	2.020000e+11	2015	12	31	South Africa	Sub-Saharan Africa	Gauteng	Witpoortjie

390 rows × 14 columns

Below, I sum all the casualities and the number of terrorist attacks or events, from each event in order to obtain their total counts. I renamed the variable for simplicity.

In [180]:
```
dfnew2014 = df_2014.groupby('country')['totalCasualities'].agg(['sum','count'
])
dfnew2015 = df_2015.groupby('country')['totalCasualities'].agg(['sum','count'
])
dfnew2016 = df_2016.groupby('country')['totalCasualities'].agg(['sum','count'
])

dfnew2014.rename(columns={'sum':'2014_sum_of_casualities', "count": "2014_numb
er_of_terrorist_attacks"}, inplace=True)
dfnew2015.rename(columns={'sum':'2015_sum_of_casualities', "count": "2015_numb
er_of_terrorist_attacks"}, inplace=True)
dfnew2016.rename(columns={'sum':'2016_sum_of_casualities', "count": "2016_numb
er_of_terrorist_attacks"}, inplace=True)

dfnew2014.head()
```

Out[180]:

	2014_sum_of_casualities	2014_number_of_terrorist_attacks
country		
Afghanistan	9794.0	1689
Albania	3.0	2
Algeria	67.0	12
Australia	11.0	8
Azerbaijan	1.0	3

It is interesting to note the shape below. It indicates that not all of the countries in the world are observed in this dataset. This could imply that some countries do not have any terrorism at all or that there is no data on them.

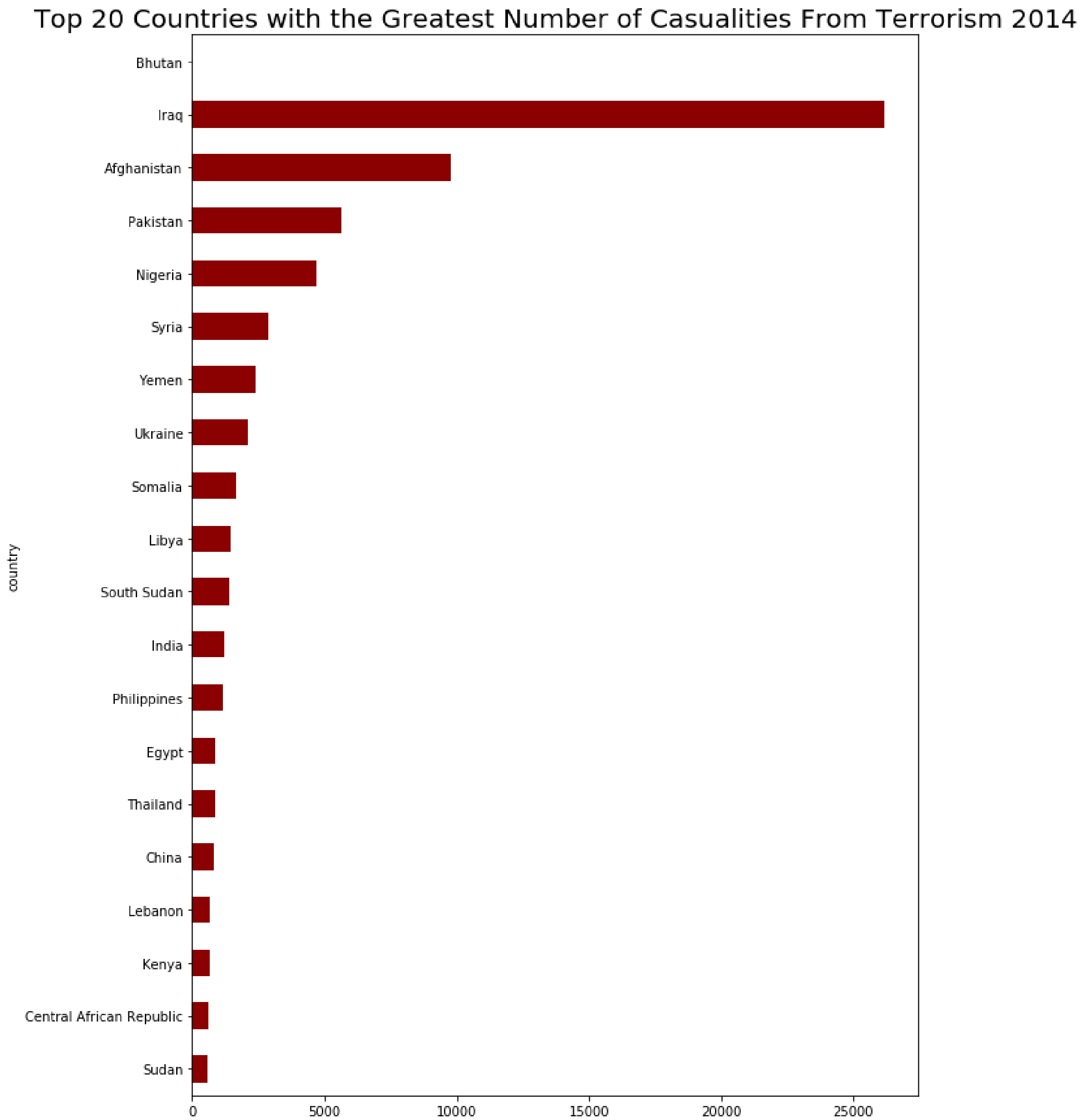
In [181]:
```
dfnew2014.shape
```

Out[181]: (98, 2)

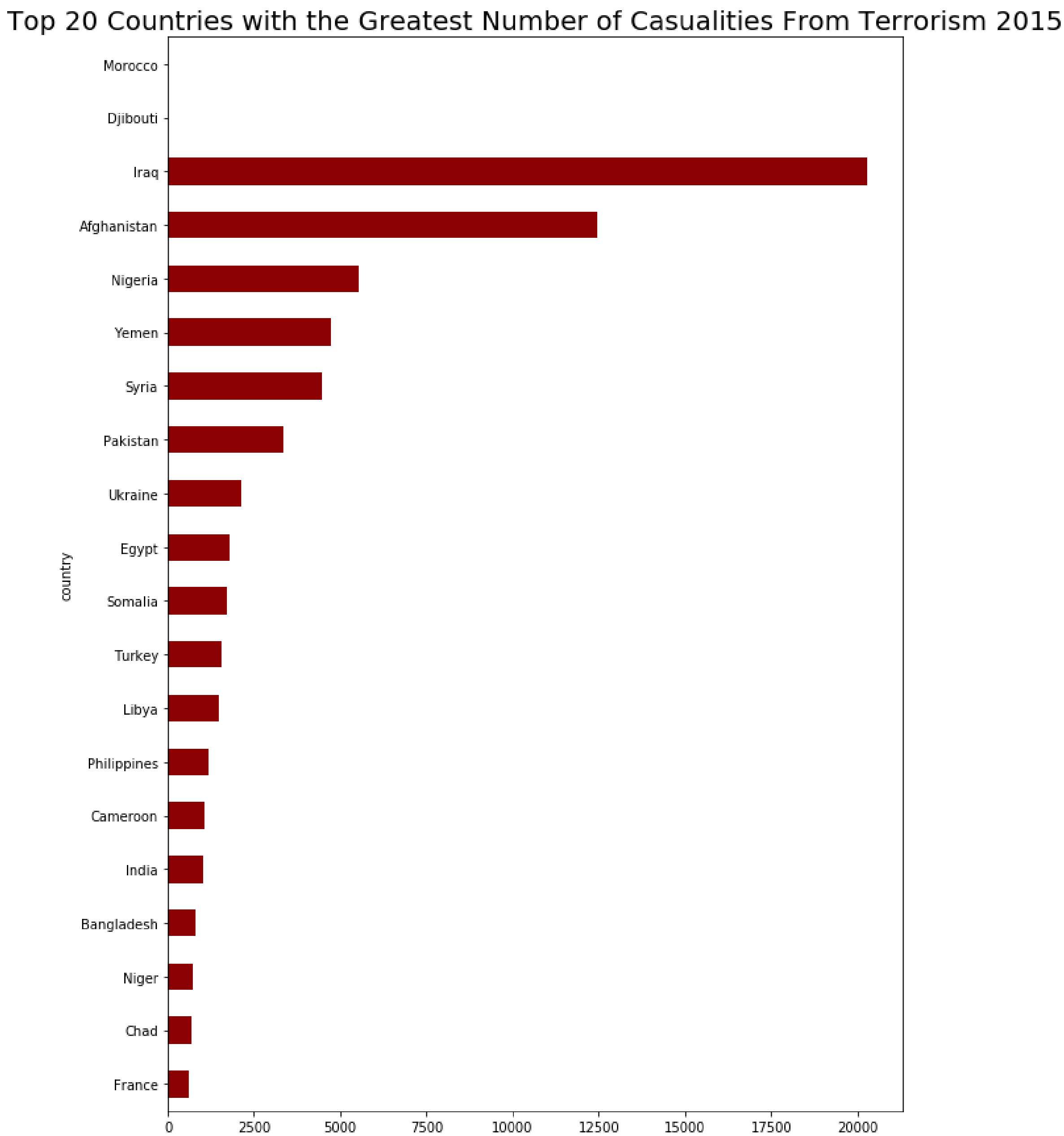
Observing Casualities From Terrorism

In this section, we will be exploring some descriptive qualities of the dataset that we are using. For each of the three years that we're exploring, I plotted the top twenty countries with the highest casualities.

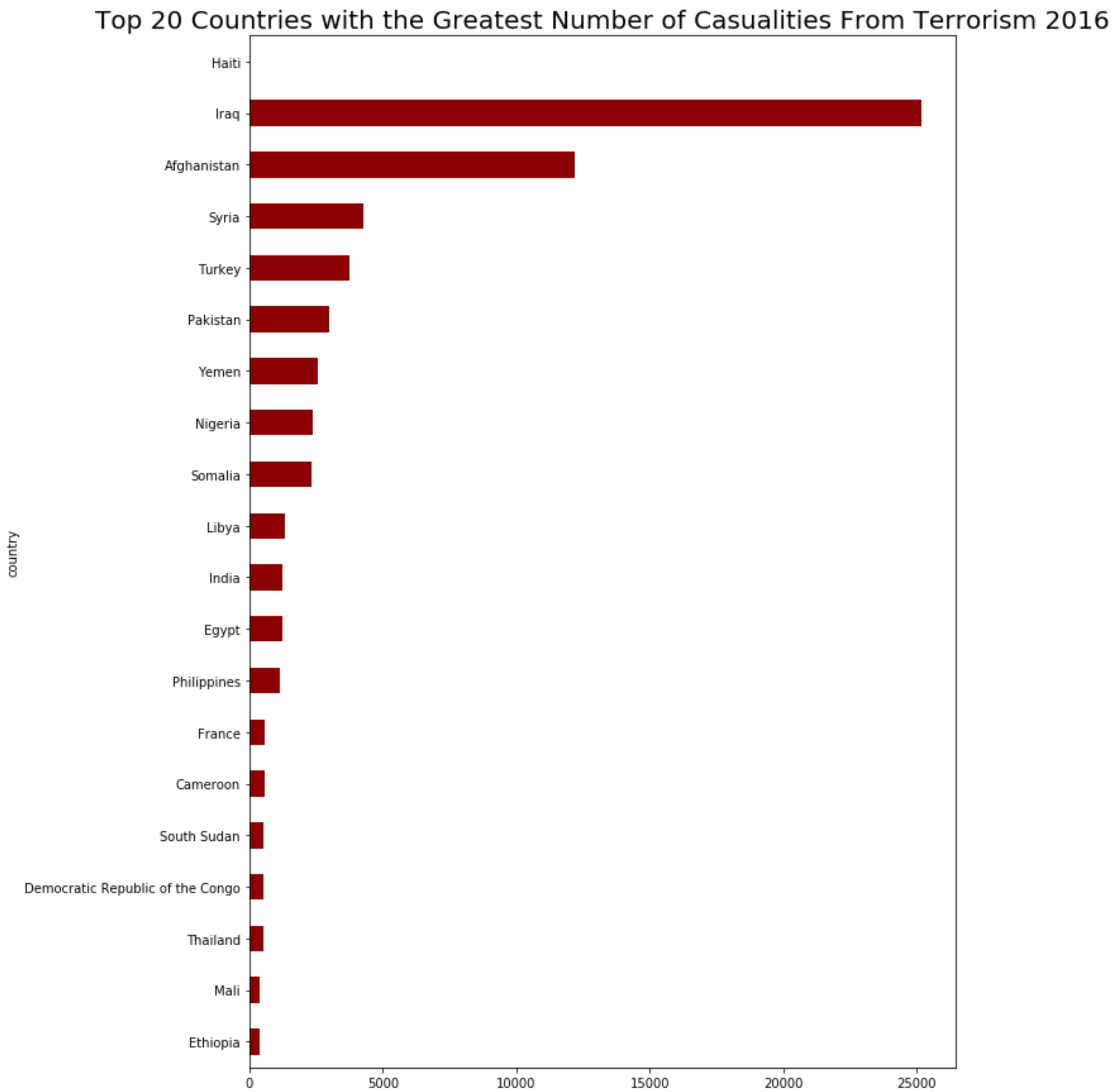
In [182]:
```
dfnew2014sorted = dfnew2014.sort_values("2014_sum_of_casualities")
dfnew2014sorted = dfnew2014sorted.tail(20)
dfnew2014sorted["2014_sum_of_casualities"].plot(kind="barh", figsize=(10, 15),
 color = "darkred")
plt.title("Top 20 Countries with the Greatest Number of Casualities From Terro
rism 2014", fontsize=20)
plt.show()
```



In [183]:
```
dfnew2015sorted = dfnew2015.sort_values("2015_sum_of_casualities")
dfnew2015sorted = dfnew2015sorted.tail(20)
dfnew2015sorted["2015_sum_of_casualities"].plot(kind="barh", figsize=(10, 15),
 color = "darkred")
plt.title("Top 20 Countries with the Greatest Number of Casualities From Terro
rism 2015", fontsize=20)
plt.show()
```



In [184]:
```
dfnew2016sorted = dfnew2016.sort_values("2016_sum_of_casualities")
dfnew2016sorted = dfnew2016sorted.tail(20)
dfnew2016sorted["2016_sum_of_casualities"].plot(kind="barh", figsize=(10, 15),
 color = "darkred")
plt.title("Top 20 Countries with the Greatest Number of Casualities From Terro
rism 2016", fontsize=20)
plt.show()
```



Observations & Analysis

- Iraq and Afghanistan have been consistently dominating the top two positions from 2014 to 2016.
- Because I am Egyptian, I am always observative of data on Egypt. It is interesting to see that Egypt's casualities from terrorism increased from 2014 to 2015, but decreased in 2016.
- Another interesting point to note is the fact that all of the countries in the top 20 bar graphs are developing countries, primarily concentrated in the Middle East, Africa, and South Asia.
- A lot of the countries listed above consistently appeared in the top 20 graphs for all three years.

Global Distribution of Terrorist Attacks

In this section, we will continue to familiarize ourselves with the data. We do so by plotting each terrorist event in its respective year's graph from 2014 to 2016 to observe the density of terrorist attacks. This will tell us where these attacks tend to concentrate, if they do in a specific region or area.

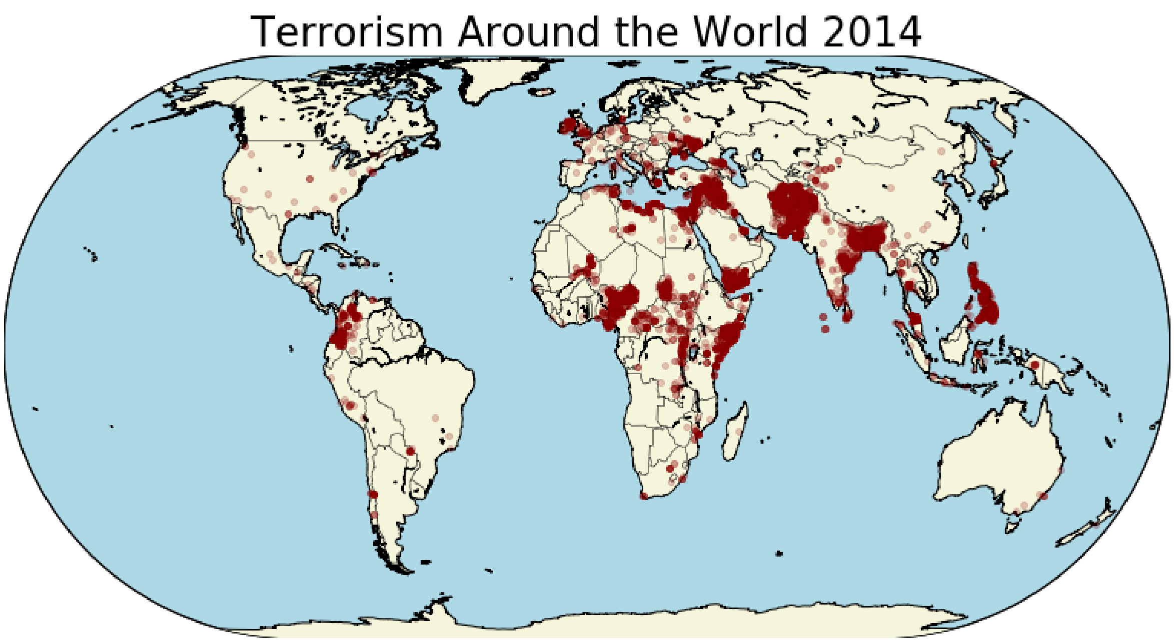
In [185]:
```
df5 = df1[df1.year==2014]
```

In [186]:
```
plt.figure(figsize=(17, 7))
m = Basemap(projection='eck4',lon_0=0,resolution='l')
m.drawcoastlines()
m.drawcountries()
m.fillcontinents(color='beige',lake_color='lightblue', zorder = 1)
m.drawmapboundary(fill_color='lightblue')
x, y = m(list(df5["longitude"].values), (list(df5["latitude"].values)))
m.plot(x, y, "o", markersize = 4, color = "darkred", alpha = .2, zorder=5)

plt.title("Terrorism Around the World 2014", fontsize=26)
plt.show()
```

```
C:\Users\Rayan\Anaconda3\lib\site-packages\mpl_toolkits\basemap\__init__.py:1
711: MatplotlibDeprecationWarning:

The axesPatch function was deprecated in version 2.1. Use Axes.patch instead.
```



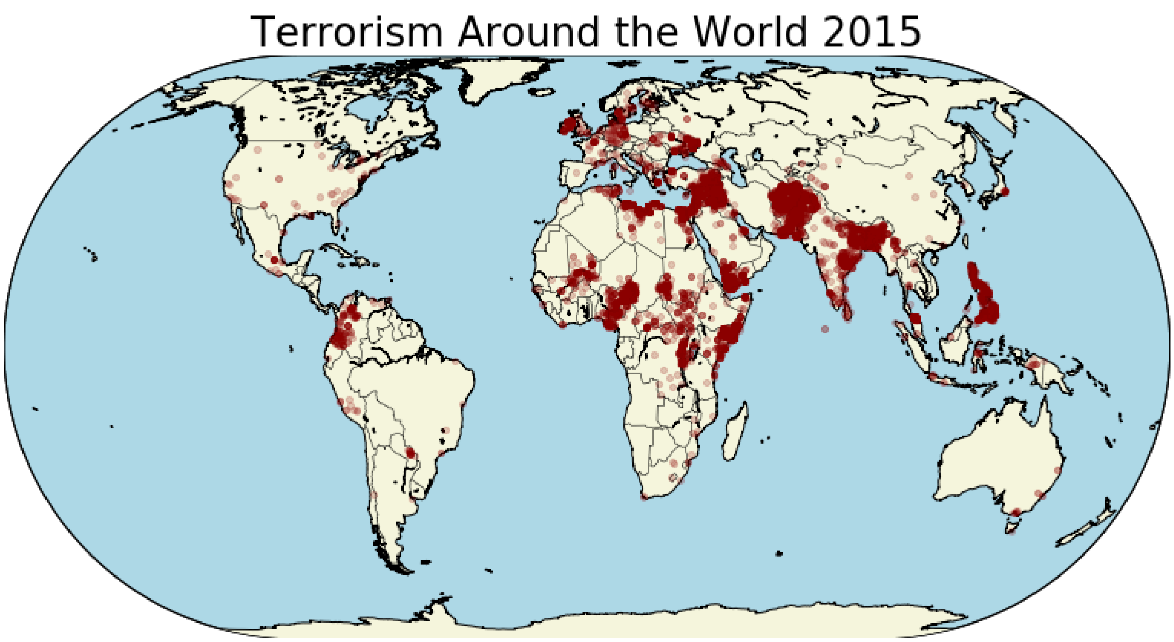
In [187]:
```
df2 = df1[df1.year==2015]
```

In [188]:
```
plt.figure(figsize=(17, 7))
m = Basemap(projection='eck4',lon_0=0,resolution='l')
m.drawcoastlines()
m.drawcountries()
m.fillcontinents(color='beige',lake_color='lightblue', zorder = 1)
m.drawmapboundary(fill_color='lightblue')
x, y = m(list(df2["longitude"].values), (list(df2["latitude"].values)))
m.plot(x, y, "o", markersize = 4, color = "darkred", alpha = .2, zorder=5)

plt.title("Terrorism Around the World 2015", fontsize=26)
plt.show()
```

```
C:\Users\Rayan\Anaconda3\lib\site-packages\mpl_toolkits\basemap\__init__.py:1
711: MatplotlibDeprecationWarning:

The axesPatch function was deprecated in version 2.1. Use Axes.patch instead.
```



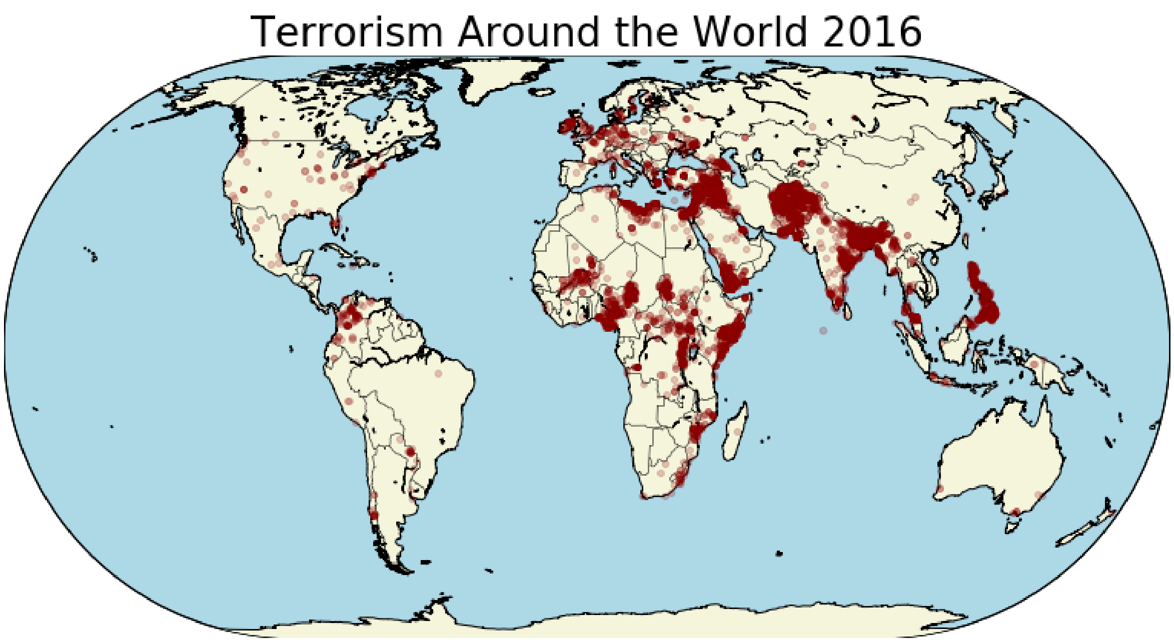
In [189]:
```
df4 = df1[df1.year==2016]
```

In [190]:
```
plt.figure(figsize=(17, 7))
m = Basemap(projection='eck4',lon_0=0,resolution='l')
m.drawcoastlines()
m.drawcountries()
m.fillcontinents(color='beige',lake_color='lightblue', zorder = 1)
m.drawmapboundary(fill_color='lightblue')
x, y = m(list(df4["longitude"].values), (list(df4["latitude"].values)))
m.plot(x, y, "o", markersize = 4, color = "darkred", alpha = .2, zorder=5)

plt.title("Terrorism Around the World 2016", fontsize=26)
plt.show()
```

```
C:\Users\Rayan\Anaconda3\lib\site-packages\mpl_toolkits\basemap\__init__.py:1
711: MatplotlibDeprecationWarning:

The axesPatch function was deprecated in version 2.1. Use Axes.patch instead.
```



Observations & Analysis

- Generally speaking, the regions that are densely populated with dots, representing terrorist attacks, are consistent over the course of the three years. Of course, there are some varying regions, some of which are pointed out below.
- In South America, the number of terrorist attacks greatly decreased from 2014 to 2016. Please keep in mind that just because the terrorist attacks have decreased, does not mean that these countries are politically more stable now. More on this discussion in the next section.
- Terrorist attacks have migrated down the South-Eastern coast of Africa from 2014 to 2016.
- The great number of terrorist attacks that concentrated around the Nile River in both Egypt and Sudan decreased from 2015 to 2016.
- Ireland has an extremely high terrorism density. I find this interesting because I don't really hear much about it on the news.
- Terrorism in Europe has increased gradually from 2014 to 2016.
- Regions with extremely high terrorism density include the Middle Eastern Gulf, South Asia (near and in Pakistan and India), Central Africa, and the United Kingdom.

Political Stability & Terrorism

As previously mentioned, political stability is explored using the Political Stability Index (PSI). Below, I retrieve the data and set it up in a dataframe.

In [191]:
```
url2 = "https://github.com/rsharkawy/Data-Bootcamp-Final-Project/blob/master/c
ountrypsi20142016.csv"

df_psi = pd.read_csv(url2, low_memory=False, encoding='ISO-8859-1')
```

```
---------------------------------------------------------------------------
ParserError                               Traceback (most recent call last)
<ipython-input-191-ac6cdc30fd2c> in <module>()
      1 url2 = "https://github.com/rsharkawy/Data-Bootcamp-Final-Project/blo
b/master/countrypsi20142016.csv"
      2 
----> 3 df_psi = pd.read_csv(url2, low_memory=False, encoding='ISO-8859-1')

C:\Users\Rayan\Anaconda3\lib\site-packages\pandas\io\parsers.py in parser_f(f
ilepath_or_buffer, sep, delimiter, header, names, index_col, usecols, squeez
e, prefix, mangle_dupe_cols, dtype, engine, converters, true_values, false_va
lues, skipinitialspace, skiprows, nrows, na_values, keep_default_na, na_filte
r, verbose, skip_blank_lines, parse_dates, infer_datetime_format, keep_date_c
ol, date_parser, dayfirst, iterator, chunksize, compression, thousands, decim
al, lineterminator, quotechar, quoting, escapechar, comment, encoding, dialec
t, tupleize_cols, error_bad_lines, warn_bad_lines, skipfooter, skip_footer, d
oublequote, delim_whitespace, as_recarray, compact_ints, use_unsigned, low_me
mory, buffer_lines, memory_map, float_precision)
    703                     skip_blank_lines=skip_blank_lines)
    704 
--> 705         return _read(filepath_or_buffer, kwds)
    706 
    707     parser_f.__name__ = name

C:\Users\Rayan\Anaconda3\lib\site-packages\pandas\io\parsers.py in _read(file
path_or_buffer, kwds)
    449 
    450     try:
--> 451         data = parser.read(nrows)
    452     finally:
    453         parser.close()

C:\Users\Rayan\Anaconda3\lib\site-packages\pandas\io\parsers.py in read(self,
 nrows)
   1063                 raise ValueError('skipfooter not supported for iterat
ion')
   1064 
-> 1065         ret = self._engine.read(nrows)
   1066 
   1067         if self.options.get('as_recarray'):

C:\Users\Rayan\Anaconda3\lib\site-packages\pandas\io\parsers.py in read(self,
 nrows)
   1826     def read(self, nrows=None):
   1827         try:
-> 1828             data = self._reader.read(nrows)
   1829         except StopIteration:
   1830             if self._first_chunk:

pandas\_libs\parsers.pyx in pandas._libs.parsers.TextReader.read()

pandas\_libs\parsers.pyx in pandas._libs.parsers.TextReader._read_rows()

pandas\_libs\parsers.pyx in pandas._libs.parsers.raise_parser_error()

ParserError: Error tokenizing data. C error: Expected 1 fields in line 116, s
aw 3
```

We continue to observe our data below. psi is short for the Political Stability Index. WBCode is a three letter country code, unique to each country. This is used in plotting geographic or spatial graphs as we will see later.

In [201]:
```
df_psindex = df_psi
df_psindex.head()
```

Out[201]:

	country	2014_psi	2015_psi	2016_psi	WBCode
country					
Aruba	Aruba	1.16	1.23	1.28	ABW
Andorra	Andorra	1.29	1.39	1.40	ADO
Afghanistan	Afghanistan	-2.41	-2.57	-2.75	AFG
Angola	Angola	-0.33	-0.50	-0.39	AGO
Anguilla	Anguilla	1.16	1.25	1.31	AIA

In [200]:
```
dfnew2014.head() #reminding ourselves of what this dataframe from before looks like.
                  #going to merge this dataframe soon
```

Out[200]:

	2014_sum_of_casualities	2014_number_of_terrorist_attacks
country		
Afghanistan	9794.0	1689
Albania	3.0	2
Algeria	67.0	12
Australia	11.0	8
Azerbaijan	1.0	3

In [ ]:
```
df_psindex.index = df_psindex["country"] #setting the index so that I can merge on it later
df_psindex.head()
```

Now we will concatenate the dataframes containing the aggregate casualities, with the dataframe containing the political stability index.

In [ ]:
```
frames14 = [dfnew2014, df_psindex]
frames15 = [dfnew2015, df_psindex]
frames16 = [dfnew2016, df_psindex]

combo2014 = pd.concat(frames14, axis=1, join='inner')
combo2015 = pd.concat(frames15, axis=1, join='inner')
combo2016 = pd.concat(frames16, axis=1, join='inner')

combo2014.head()
```

In [ ]:
```
combo2014.rename(columns={'WBCode':'iso_a3'}, inplace=True) #renaming the vari
ables in order for them to match the next dataset
combo2015.rename(columns={'WBCode':'iso_a3'}, inplace=True)
combo2016.rename(columns={'WBCode':'iso_a3'}, inplace=True)

combo2014.head()
```

world is a Geodataframe, meaning it contains geospatial attributes that are used in plotting geographic maps. After initializing world, we create a copy of it containing only two of its attributes: geometry and iso_a3. The geometry attribute is essentially the polygon shape of each country on a map. This is crucial in creating chloropleth maps, which is what we will produce in a few steps. iso_a3 is the unique three letter country code attributed to each country.

We use the .head() function to explore what the Geodataframe contains.

In [204]:
```
world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))
world.head()
```

Out[204]:

	pop_est	continent	name	iso_a3	gdp_md_est	geometry
0	28400000.0	Asia	Afghanistan	AFG	22270.0	POLYGON ((61.21081709172574 35.65007233330923,...
1	12799293.0	Africa	Angola	AGO	110300.0	(POLYGON ((16.32652835456705 -5.87747039146621...
2	3639453.0	Europe	Albania	ALB	21810.0	POLYGON ((20.59024743010491 41.85540416113361,...
3	4798491.0	Asia	United Arab Emirates	ARE	184300.0	POLYGON ((51.57951867046327 24.24549713795111,...
4	40913584.0	South America	Argentina	ARG	573900.0	(POLYGON ((-65.50000000000003 -55.199999999999...

In [205]:
```
type(world) #confirming the type
```

Out[205]:
```
geopandas.geodataframe.GeoDataFrame
```

We merge each year's data with world on the country code: iso_a3. We do this in order to have a complete dataset that allows for the mapping of a country's polygon to a country's data records: PSI, aggregate casualities, etc.

In [ ]:
```
country_polygons = world[['geometry', 'iso_a3']]

country_polygons2014 = country_polygons
country_polygons2015 = country_polygons
country_polygons2016 = country_polygons

country_polygons2014 = country_polygons2014.merge(combo2014, on="iso_a3")
country_polygons2015 = country_polygons2015.merge(combo2015, on="iso_a3")
country_polygons2016 = country_polygons2016.merge(combo2016, on="iso_a3")

country_polygons2014.head()
```

We will now create three chloropleth graphs, one for each year we are observing. The shading and hue of the countries informs us about their PSI. Blue indicates a positive PSI which portrays a greater level of political stability. Red indicates a negative PSI, indicating a greater level of political instability. The minimum and maximum values for PSI are -2.5 and 2.5 respectively.

On top of the chloropleth map, we include a scatterplot layer. Each dot indicates a terrorist event. Moreover, this is plotting terrorism density on top of political stability index.

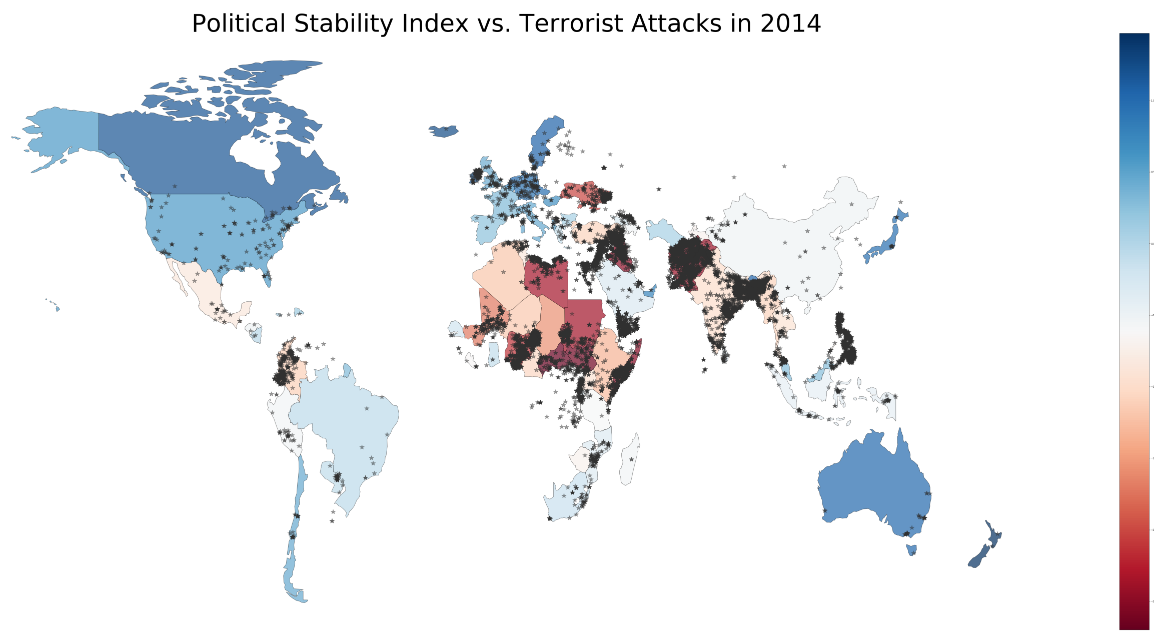
In [206]:
```
fig, ax = plt.subplots(figsize=(100, 45))
country_polygons2014.plot(ax=ax, edgecolor="black", column = "2014_psi", alpha
 = 0.7, legend=True, cmap = "RdBu")
plt.title("Political Stability Index vs. Terrorist Attacks in 2014", fontsize=
100)

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

ax.get_xaxis().set_visible(False)
ax.get_yaxis().set_visible(False)

x = list(df1["longitude"].values)
y = list(df1["latitude"].values)
ax.plot(x, y, marker='*', linestyle="none", color='#303030', markersize=20, al
pha=0.5);

plt.show()
```



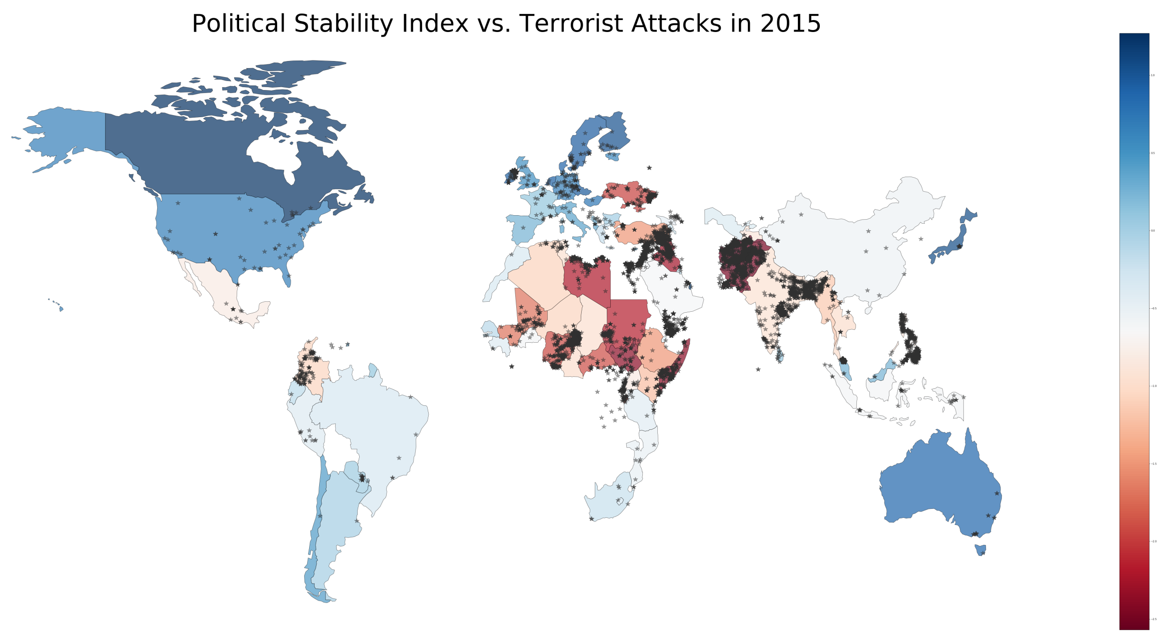
In [192]:
```
fig, ax = plt.subplots(figsize=(100, 45))
country_polygons2015.plot(ax=ax, edgecolor="black", column = "2015_psi", alpha
 = 0.7, legend=True, cmap = "RdBu")
plt.title("Political Stability Index vs. Terrorist Attacks in 2015", fontsize=
100)

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

ax.get_xaxis().set_visible(False)
ax.get_yaxis().set_visible(False)

x = list(df2["longitude"].values)
y = list(df2["latitude"].values)
ax.plot(x, y, marker='*', linestyle="none", color='#303030', markersize=20, al
pha=0.5);

plt.show()
```



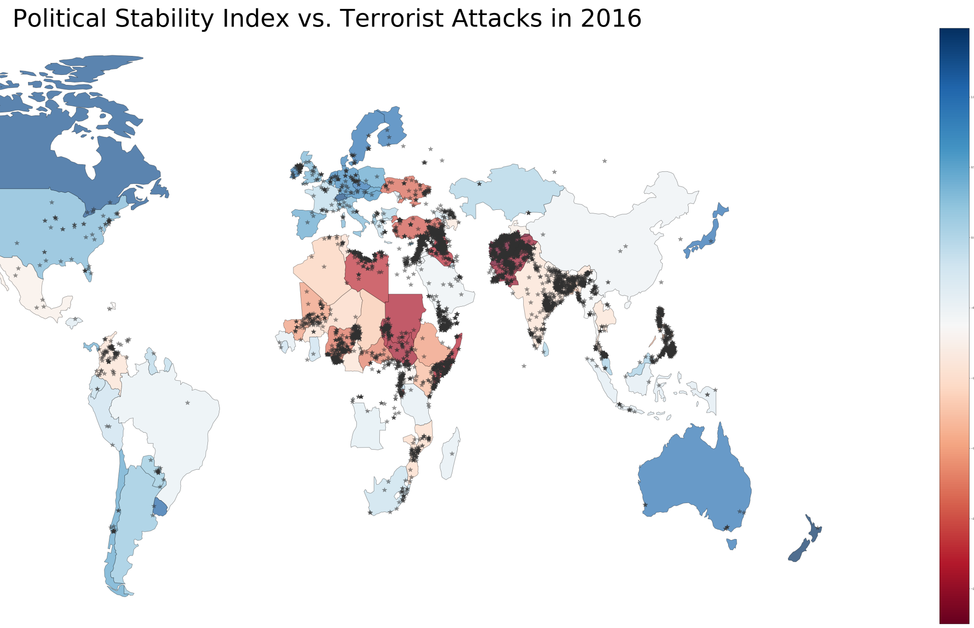
In [193]:
```
fig, ax = plt.subplots(figsize=(100, 45))
country_polygons2016.plot(ax=ax, edgecolor="black", column = "2016_psi", alpha
 = 0.7, legend=True, cmap = "RdBu")
plt.title("Political Stability Index vs. Terrorist Attacks in 2016", fontsize=
100)

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

ax.get_xaxis().set_visible(False)
ax.get_yaxis().set_visible(False)

x = list(df4["longitude"].values)
y = list(df4["latitude"].values)
ax.plot(x, y, marker='*', linestyle="none", color='#303030', markersize=20, al
pha=0.5);

plt.show()
```



Observations & Analysis

Since we've previously discussed terrorism density and its global distribution, this section will first focus on the political stability index, and then on its descriptive relationship with terrorism density.

- Central and Subsaharan Africa is quite politically unstable as indicated by the great area shaded red. However, the political instability in this area decreased gradually from 2014 to 2016.
- Japan, Europe, USA, Canada, Australia, and New Zealand are the most politically stable countries. All of these countries are developed countries which then raises the question: what is the relationship and correlation between how developed (presumably economically) a country is and its political stability? We leave this question for future research.
- Personal side note: I am beginning to doubt the accuracy of the political stability index. This chloropleth map shows countries like Venezuala and Macedonia, which have been experiencing lots of governmental conflict, revolutions, political instability, etc. for the past few years, as pale pink and light blue respectively.
- Countries without PSI data are not drawn (white background).
- Notice how countries in Subsaharan Africa, the Middle Eastern Gulf and South Asia with high political instability also have high terrorism density.
- Contrary to the previous observation, some countries in Europe, such as Ireland, which have a high terrorism density, simultaneously have low political instability (high PSI).

Beyond this descriptive analysis, we must investigate some statistical relationships between terrorism and PSI to better comprehend their dynamic.

Regression Analysis

Regressing Political Stability Index (PSI) on Total Terrorism Casualities

This section regresses PSI on terrorism, measured as aggregated casualities per country. We will observe the regression for each of the three year's data to see if there are any significant differences between those points in time.

In [194]:
```
#Regression of the Sum of Casualities by Country in 2014, and each country's P
olitical Stability Index (PSI) in 2014
reg2014 = country_polygons2014[["2014_sum_of_casualities", "2014_psi"]]
reg2014.columns = ["sumcas", "psi"]

#changing their names so that its easier to run ols regression
results2014 = smf.ols(formula = "psi ~ sumcas", data= reg2014).fit()

print("Year: 2014")
print("Parameters: ")
print(results2014.params)
print("Summary Results: ")
print(results2014.summary())
#Estimating the linear relationship
```

```
Year: 2014
Parameters:
Intercept   -0.382676
sumcas      -0.000134
dtype: float64
Summary Results:
                            OLS Regression Results

==============================================================================
=
Dep. Variable:                    psi   R-squared:                       0.16
8
Model:                            OLS   Adj. R-squared:                  0.15
7
Method:                 Least Squares   F-statistic:                     15.9
1
Date:                Fri, 22 Dec 2017   Prob (F-statistic):           0.00014
8
Time:                        00:09:38   Log-Likelihood:                -110.1
3
No. Observations:                  81   AIC:                             224.
3
Df Residuals:                      79   BIC:                             229.
0
Df Model:                           1

Covariance Type:            nonrobust

==============================================================================
=
                 coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
-
Intercept     -0.3827      0.109     -3.508      0.001      -0.600      -0.16
6
sumcas        -0.0001   3.37e-05     -3.989      0.000      -0.000   -6.72e-0
5
==============================================================================
=
Omnibus:                        0.977   Durbin-Watson:                   2.02
4
Prob(Omnibus):                  0.614   Jarque-Bera (JB):                1.01
9
Skew:                          -0.153   Prob(JB):                        0.60
1
Kurtosis:                       2.544   Cond. No.                     3.34e+0
3
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 3.34e+03. This might indicate that there a
re
strong multicollinearity or other numerical problems.
```

In [195]:
```
#Regression of the Sum of Casualities by Country in 2015, and each country's P
olitical Stability Index (PSI) in 2015
reg2015 = country_polygons2015[["2015_sum_of_casualities", "2015_psi"]]
reg2015.columns = ["sumcas", "psi"]

results2015 = smf.ols(formula = "psi ~ sumcas", data= reg2015).fit()

print("Year: 2015")
print("Parameters: ")
print(results2015.params)
print("Summary Results: ")
print(results2015.summary())
#Estimating the linear relationship
```

```
Year: 2015
Parameters:
Intercept   -0.370282
sumcas      -0.000161
dtype: float64
Summary Results:
                            OLS Regression Results

==============================================================================
=
Dep. Variable:                    psi   R-squared:                       0.19
1
Model:                            OLS   Adj. R-squared:                  0.18
0
Method:                 Least Squares   F-statistic:                     18.1
5
Date:                Fri, 22 Dec 2017   Prob (F-statistic):           5.73e-0
5
Time:                        00:09:39   Log-Likelihood:                -103.6
1
No. Observations:                  79   AIC:                             211.
2
Df Residuals:                      77   BIC:                             216.
0
Df Model:                           1

Covariance Type:            nonrobust

==============================================================================
=
                 coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
-
Intercept     -0.3703      0.106     -3.482      0.001      -0.582      -0.15
9
sumcas        -0.0002   3.77e-05     -4.260      0.000      -0.000   -8.55e-0
5
==============================================================================
=
Omnibus:                        3.789   Durbin-Watson:                   2.05
5
Prob(Omnibus):                  0.150   Jarque-Bera (JB):                2.10
2
Skew:                          -0.120   Prob(JB):                        0.35
0
Kurtosis:                       2.238   Cond. No.                     2.93e+0
3
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 2.93e+03. This might indicate that there a
re
strong multicollinearity or other numerical problems.
```

In [196]:

```
#Regression of the Sum of Casualities by Country in 2015, and each country's P
olitical Stability Index (PSI) in 2015
reg2016 = country_polygons2016[["2016_sum_of_casualities", "2016_psi"]]
reg2016.columns = ["sumcas", "psi"]

results2016 = smf.ols(formula = "psi ~ sumcas", data= reg2016).fit()

print("Year: 2016")
print("Parameters: ")
print(results2016.params)
print("Summary Results: ")
print(results2016.summary())
#Estimating the linear relationship
```

```
Year: 2016
Parameters:
Intercept   -0.319002
sumcas      -0.000133
dtype: float64
Summary Results:
                            OLS Regression Results

==============================================================================
=
Dep. Variable:                    psi   R-squared:                       0.15
1
Model:                            OLS   Adj. R-squared:                  0.14
1
Method:                 Least Squares   F-statistic:                     15.6
4
Date:                Fri, 22 Dec 2017   Prob (F-statistic):           0.00015
4
Time:                        00:09:39   Log-Likelihood:                -121.2
0
No. Observations:                  90   AIC:                             246.
4
Df Residuals:                      88   BIC:                             251.
4
Df Model:                           1

Covariance Type:            nonrobust

==============================================================================
=
                 coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
-
Intercept     -0.3190      0.102     -3.138      0.002      -0.521      -0.11
7
sumcas        -0.0001   3.36e-05     -3.955      0.000      -0.000   -6.61e-0
5
==============================================================================
=
Omnibus:                        3.771   Durbin-Watson:                   1.96
4
Prob(Omnibus):                  0.152   Jarque-Bera (JB):                2.34
7
Skew:                          -0.181   Prob(JB):                        0.30
9
Kurtosis:                       2.296   Cond. No.                     3.10e+0
3
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 3.1e+03. This might indicate that there ar
e
strong multicollinearity or other numerical problems.
```

Observations & Analysis

- R-squared in all three regressions lies between 0.15 to 0.19, indicating that about 15-19% of the variation in the political stability index is explained by terrorism casualities.
- All of our regression coefficients and intercepts are statistically significant at the 95% confidence level. Additionally, the values for the regression coefficient are extremely small, about -0.0001. Since these values are statistically significant and very small, this means that the impact of terrorism casualities on political stability indices is extremely minor.
- All of the intercepts are approximately equivalent to -0.3 and are statistically significant as well. These intercepts are much larger than the regression coefficients, portraying how there exist other variables that have a much more potent impact on political stability indices.
- The variation between the results in the abovementioned three regressions is minimal.

Regressing Total Terrorism Casualities on Political Stability Index (PSI)

This section regresses terrorism on PSI. We will observe the regression for each of the three year's data to see if there are any significant differences between those points in time.

In [197]:
```
#Regression of the Sum of Casualities by Country in 2014, and each country's P
olitical Stability Index (PSI) in 2014
results2014b = smf.ols(formula = "sumcas ~ psi", data= reg2014).fit()

print("Year: 2014")
print("Parameters: ")
print(results2014b.params)
print("Summary Results: ")
print(results2014b.summary())
#Estimating the linear relationship
```

```
Year: 2014
Parameters:
Intercept     157.063804
psi         -1248.863118
dtype: float64
Summary Results:
                            OLS Regression Results

==============================================================================
=
Dep. Variable:                 sumcas   R-squared:                       0.16
8
Model:                            OLS   Adj. R-squared:                  0.15
7
Method:                 Least Squares   F-statistic:                     15.9
1
Date:                Fri, 22 Dec 2017   Prob (F-statistic):           0.00014
8
Time:                        00:09:42   Log-Likelihood:                -759.9
9
No. Observations:                  81   AIC:                             152
4.
Df Residuals:                      79   BIC:                             152
9.
Df Model:                           1

Covariance Type:            nonrobust

==============================================================================
=
                 coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
-
Intercept    157.0638    357.301      0.440      0.661    -554.126     868.25
3
psi        -1248.8631    313.115     -3.989      0.000   -1872.102    -625.62
4
==============================================================================
=
Omnibus:                      144.182   Durbin-Watson:                   1.71
7
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             8049.57
4
Skew:                           6.353   Prob(JB):                        0.0
0
Kurtosis:                      50.155   Cond. No.                        1.6
1
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
```

In [198]:
```
#Regression of the Sum of Casualities by Country in 2015, and each country's P
olitical Stability Index (PSI) in 2015
results2015b = smf.ols(formula = "sumcas ~ psi", data= reg2015).fit()

print("Year: 2015")
print("Parameters: ")
print(results2015b.params)
print("Summary Results: ")
print(results2015b.summary())
#Estimating the linear relationship
```

```
Year: 2015
Parameters:
Intercept     178.284426
psi         -1188.072171
dtype: float64
Summary Results:
                            OLS Regression Results

=============================================================================
=
Dep. Variable:                 sumcas   R-squared:                      0.19
1
Model:                            OLS   Adj. R-squared:                 0.18
0
Method:                 Least Squares   F-statistic:                    18.1
5
Date:                Fri, 22 Dec 2017   Prob (F-statistic):         5.73e-0
5
Time:                        00:09:43   Log-Likelihood:               -728.3
9
No. Observations:                  79   AIC:                            146
1.
Df Residuals:                      77   BIC:                            146
6.
Df Model:                           1

Covariance Type:            nonrobust

=============================================================================
=
                 coef    std err          t      P>|t|      [0.025      0.97
5]
-----------------------------------------------------------------------------
-
Intercept    178.2844    310.546      0.574      0.568    -440.091     796.66
0
psi       -1188.0722    278.898     -4.260      0.000   -1743.429    -632.71
6
=============================================================================
=
Omnibus:                      123.242   Durbin-Watson:                  1.80
4
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            3827.53
3
Skew:                           5.226   Prob(JB):                        0.0
0
Kurtosis:                      35.458   Cond. No.                        1.6
3
=============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
```

In [199]:
```
#Regression of the Sum of Casualities by Country in 2016, and each country's P
olitical Stability Index (PSI) in 2016
results2016b = smf.ols(formula = "sumcas ~ psi", data= reg2016).fit()

print("Year: 2016")
print("Parameters: ")
print(results2016b.params)
print("Summary Results: ")
print(results2016b.summary())
#Estimating the linear relationship
```

```
Year: 2016
Parameters:
Intercept     201.449448
psi         -1136.195079
dtype: float64
Summary Results:
                            OLS Regression Results                            
                                                                              
==============================================================================
=
Dep. Variable:                 sumcas   R-squared:                       0.15
1
Model:                            OLS   Adj. R-squared:                  0.14
1
Method:                 Least Squares   F-statistic:                     15.6
4
Date:                Fri, 22 Dec 2017   Prob (F-statistic):           0.00015
4
Time:                        00:09:44   Log-Likelihood:                -839.4
8
No. Observations:                  90   AIC:                             168
3.
Df Residuals:                      88   BIC:                             168
8.
Df Model:                           1                                         

Covariance Type:            nonrobust                                         

==============================================================================
=
                 coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
-
Intercept    201.4494    312.733      0.644      0.521    -420.042     822.94
1
psi        -1136.1951    287.277     -3.955      0.000   -1707.098    -565.29
2
==============================================================================
=
Omnibus:                      157.367   Durbin-Watson:                   1.85
8
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             9757.44
6
Skew:                           6.529   Prob(JB):                         0.0
0
Kurtosis:                      52.310   Cond. No.                         1.5
0
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
```

Observations & Analysis

- R-squared in all three regressions is the same as previously discussed for obvious statistical reasons; it lies between 0.15 to 0.19, indicating that about 15-19% of the variation in the political stability index is explained by terrorism casualities.
- All of our regression coefficients are statistically significant at the 95% confidence level. Additionally, the values for the regression coefficient are extremely large in the absolute value sense. They range from about -1200 to -1100. Since these values are statistically significant and very large, this means that the impact of political stability on terrorism casualities indices is quite large. Moreover, the variables are inversely correlated.
- None of the intercepts are statistically significant. These intercepts are much smaller than the regression coefficients, portraying how there exist some other variables that explain terrorism casualities.
- The variation between the results in the abovementioned three regressions is minimal.

Summary & Concluding Remarks

Now that we have gone through all the data visualization and analysis, we will recap the key points and then propose areas for further research.

From our descriptive analysis, we learned that most countries' in the top 20 countries for total casualities caused by terrorism, consistently appeared in the top 20 from 2014 to 2015. Next, we observed terrorism density and its global distribution, which revealed to us which regions experience a greater number of terrorist events and attacks. Then, we visually compared terrorism density to the political stability index and we noticed that many countries with high terrorism density also had a low PSI. However, what was interesting to note is how some countries like Ireland, are very politcally stable, yet they experience a significant amount of terrorism. After that we resorted to a more quantitative analytical approach through OLS regressions. We learned that although terrorism does not explain much of political instability, political stability holds a strong inverse relationship with terrorism casualities.

Further Investigation

Below I have added some questions I came up with for future research to expand on this project...

- What is the relationship between how developed a country is and its political stability? What factors contribute to a high PSI?
- What is the impact of terrorism and its casualities on the investment climate, observed through sovreign credit risk ratings and stock indices?
  - Note: I primarily wanted to research this question. However, I could not find any accessible data online to perform such analysis. All historical data on credit ratings are locked and sold for a significant charge. With regards to stock indices, it is extremely difficult to find historical data on stock index performance for the indices outside of the USA.
- How are different types of terrorism distributed globally? Do some types concentrate in specific regions?

```
In [ ]:
```