Analysis of Leading Causes of Death

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Around 3 million Americans die each year, which means that the death rate is about 860 deaths per 100,000 people. The goal of our project is to take a closer look at the causal factors for these deaths across the US and analyze this data to see what factors pose a higher risk. Additionally, we explore these factors in the smaller region of New York City and compare it with the nationwide results. https://www.cdc.gov/nchs/fastats/deaths.htm

I. Introduction to Mortality Data

In [1]:
```
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
import numpy as np
import statsmodels.formula.api as smf
import seaborn as sb
import copy
from IPython.display import display
import plotly.graph_objects as go

%matplotlib inline
```

Data Sources

NYC mortality source: https://data.cityofnewyork.us/Health/New-York-City-Leading-Causes-of-Death/jb7j-dtam

US mortality source: https://catalog.data.gov/dataset/age-adjusted-death-rates-for-the-top-10-leading-causes-of-death-united-states-2013

First, we need to read and clean the csv files by changing datatypes, correcting spelling, and checking for repetitions or unique characteristics. Here, we are going through our NYC and US datasets.

New York City Data

In [2]:
```
nyc = pd.read_csv("nyc.csv")
nyc = nyc.replace(".",0)
nyc = nyc.astype({'Deaths': 'float64', 'Death Rate': 'float64', "Age Ad
justed Death Rate":"float64"})
nyc
```

Out[2]:

	Year	Leading Cause	Sex	Race Ethnicity	Deaths	Death Rate	Age Adjusted Death Rate
0	2010	Influenza (Flu) and Pneumonia (J09-J18)	F	Hispanic	228.0	18.7	23.1
1	2008	Accidents Except Drug Posioning (V01-X39, X43,...	F	Hispanic	68.0	5.8	6.6
2	2013	Accidents Except Drug Posioning (V01-X39, X43,...	M	White Non-Hispanic	271.0	20.1	17.9
3	2010	Cerebrovascular Disease (Stroke: I60-I69)	M	Hispanic	140.0	12.3	21.4
4	2009	Assault (Homicide: Y87.1, X85-Y09)	M	Black Non-Hispanic	255.0	30.0	30.0
...	...	...	...	...	...	...	...

	Year	Leading Cause	Sex	Race Ethnicity	Deaths	Death Rate	Age Adjusted Death Rate
1089	2012	Influenza (Flu) and Pneumonia (J09-J18)	F	Not Stated/Unknown	6.0	0.0	0.0
1090	2014	Accidents Except Drug Posioning (V01-X39, X43,...	F	White Non-Hispanic	169.0	11.9	7.4
1091	2009	Malignant Neoplasms (Cancer: C00-C97)	M	White Non-Hispanic	3236.0	240.5	205.6
1092	2009	Intentional Self-Harm (Suicide: X60-X84, Y87.0)	M	White Non-Hispanic	191.0	14.2	13.0
1093	2013	Essential Hypertension and Renal Diseases (I10...	M	Black Non-Hispanic	148.0	17.2	20.9

1094 rows × 7 columns

In [3]:
```
nyc.dtypes
```

Out[3]:
```
Year                         int64
Leading Cause               object
Sex                         object
Race Ethnicity              object
Deaths                     float64
Death Rate                 float64
Age Adjusted Death Rate    float64
dtype: object
```

In [4]:
```
#misspelled "poisoning"
nyc["Leading Cause"] = nyc["Leading Cause"].replace("Accidents Except D
rug Posioning (V01-X39, X43, X45-X59, Y85-Y86)","Accidents Except Drug
 Poisoning (V01-X39, X43, X45-X59, Y85-Y86)")
```

In [5]:
```
print(nyc["Race Ethnicity"].unique())
print(nyc['Sex'].unique())
print(nyc['Year'].unique())
```

```
['Hispanic' 'White Non-Hispanic' 'Black Non-Hispanic'
```

```
 'Other Race/ Ethnicity' 'Asian and Pacific Islander' 'Not Stated/Unkno
wn']
['F' 'M']
[2010 2008 2013 2009 2012 2011 2014 2007]
```

US Data

In [6]:
```
us = pd.read_csv('agg.csv')
us
```

Out[6]:

	Year	113 Cause Name	Cause Name	State	Deaths	Age-adjusted Death Rate
0	2017	Accidents (unintentional injuries) (V01-X59,Y8...	Unintentional injuries	United States	169,936	49.4
1	2017	Accidents (unintentional injuries) (V01-X59,Y8...	Unintentional injuries	Alabama	2,703	53.8
2	2017	Accidents (unintentional injuries) (V01-X59,Y8...	Unintentional injuries	Alaska	436	63.7
3	2017	Accidents (unintentional injuries) (V01-X59,Y8...	Unintentional injuries	Arizona	4,184	56.2
4	2017	Accidents (unintentional injuries) (V01-X59,Y8...	Unintentional injuries	Arkansas	1,625	51.8
...	...	...	...	...	...	...
10863	1999	Nephritis, nephrotic syndrome and nephrosis (N...	Kidney disease	Virginia	1,035	16.9
10864	1999	Nephritis, nephrotic syndrome and nephrosis (N...	Kidney disease	Washington	278	5.2
10865	1999	Nephritis, nephrotic syndrome and nephrosis (N...	Kidney disease	West Virginia	345	16.4
10866	1999	Nephritis, nephrotic syndrome and nephrosis (N...	Kidney disease	Wisconsin	677	11.9

	Year	113 Cause Name	Cause Name	State	Deaths	Age-adjusted Death Rate
10867	1999	Nephritis, nephrotic syndrome and nephrosis (N...	Kidney disease	Wyoming	30	6.8

10868 rows × 6 columns

In [7]:
```
us.dtypes
```

Out[7]:
```
Year                           int64
113 Cause Name                object
Cause Name                    object
State                         object
Deaths                        object
Age-adjusted Death Rate       object
dtype: object
```

In [8]:
```
us['State'].nunique()
```

Out[8]:
```
52
```

In [9]:
```
us["State"].unique()
```

Out[9]:
```
array(['United States', 'Alabama', 'Alaska', 'Arizona', 'Arkansas',
       'California', 'Colorado', 'Connecticut', 'Delaware',
       'District of Columbia', 'Florida', 'Georgia', 'Hawaii', 'Idaho',
       'Illinois', 'Indiana', 'Iowa', 'Kansas', 'Kentucky', 'Louisian
a',
       'Maine', 'Maryland', 'Massachusetts', 'Michigan', 'Minnesota',
       'Mississippi', 'Missouri', 'Montana', 'Nebraska', 'Nevada',
       'New Hampshire', 'New Jersey', 'New Mexico', 'New York',
       'North Carolina', 'North Dakota', 'Ohio', 'Oklahoma', 'Oregon',
       'Pennsylvania', 'Rhode Island', 'South Carolina', 'South Dakot
a',
       'Tennessee', 'Texas', 'Utah', 'Vermont', 'Virginia', 'Washingto
n',
       'West Virginia', 'Wisconsin', 'Wyoming'], dtype=object)
```

All 50 states are included in the dataset, additionally the District of Columbia is included along with the total for the United States, thus making the number of unique "States" equal to 52.

Analysis: Leading Causes of Death

First, an overview of the most common causes of death in New York City versus the rest of the US.

Preparation of NYC Dataset

2010 Census Data Source: https://www.census.gov/programs-surveys/popest/data/data-sets.All.html

In [10]:

```
#change names of NYC causes to match US data
#drop the rows that are not mutual

#replace the technical cause names in the NYC dataset with the common n
ames in the US dataset
nyc.replace({'Influenza (Flu) and Pneumonia (J09-J18)':'Influenza and p
neumonia',
             'Accidents Except Drug Poisoning (V01-X39, X43, X45-X59, Y
85-Y86)':'Unintentional injuries',
             'Alzheimer\'s Disease (G30)':'Alzheimer\'s disease',
             'Cerebrovascular Disease (Stroke: I60-I69)':'Stroke',
             'Chronic Liver Disease and Cirrhosis (K70, K73)':'CLRD',
             'Diabetes Mellitus (E10-E14)':'Diabetes',
             'Diseases of Heart (I00-I09, I11, I13, I20-I51)':'Heart di
sease',
             'Influenza (Flu) and Pneumonia (J09-J18)':'Influenza and p
neumonia',
             'Intentional Self-Harm (Suicide: X60-X84, Y87.0)':'Suicid
e',
             'Malignant Neoplasms (Cancer: C00-C97)':'Cancer',
             'Nephritis, Nephrotic Syndrome and Nephrisis (N00-N07, N17
```

```
-N19, N25-N27)':'Kidney disease'},
            inplace = True)
leading_causes = "Influenza and pneumonia|Unintentional injuries|Alzhei
mer\'s disease|Stroke|CLRD|Diabetes|Heart disease|Influenza and pneumon
ia|Suicide|Cancer|Kidney disease"

#drop non mutual rows
not_using = nyc[~nyc["Leading Cause"].str.contains(leading_causes, rege
x=True)].index
nyc.drop(not_using, inplace=True)
nyc
```

Out[10]:

	Year	Leading Cause	Sex	Race Ethnicity	Deaths	Death Rate	Age Adjusted Death Rate
0	2010	Influenza and pneumonia	F	Hispanic	228.0	18.7	23.1
1	2008	Unintentional injuries	F	Hispanic	68.0	5.8	6.6
2	2013	Unintentional injuries	M	White Non-Hispanic	271.0	20.1	17.9
3	2010	Stroke	M	Hispanic	140.0	12.3	21.4
6	2012	Stroke	F	Asian and Pacific Islander	102.0	17.5	20.7
...	...	...	...	...	...	...	...
1088	2008	CLRD	F	Other Race/ Ethnicity	0.0	0.0	0.0
1089	2012	Influenza and pneumonia	F	Not Stated/Unknown	6.0	0.0	0.0
1090	2014	Unintentional injuries	F	White Non-Hispanic	169.0	11.9	7.4
1091	2009	Cancer	M	White Non-Hispanic	3236.0	240.5	205.6
1092	2009	Suicide	M	White Non-Hispanic	191.0	14.2	13.0

666 rows × 7 columns

Preparation of US Dataset

Our target time frame are the years 2008-2014. These years overlap in our data sets, so we will be using them to conduct our analysis to ensure accurate data.

In [11]:
```
print("nyc sets years: ",nyc["Year"].unique())
print("us sets years: ", us["Year"].unique())
```

```
nyc sets years:  [2010 2008 2013 2012 2009 2011 2014 2007]
us sets years:  [2017 2016 2015 2014 2013 2012 2011 2010 2009 2008 2007
2006 2005 2004
 2003 2002 2001 2000 1999]
```

In [12]:
```
#get matching years from US data
#remove 113 cause name
us = us.loc[us["Year"] > 2007]
us = us.loc[us["Year"] < 2015]
del us["113 Cause Name"]
us
```

Out[12]:

	Year	Cause Name	State	Deaths	Age-adjusted Death Rate
1716	2014	Unintentional injuries	Alabama	2,463	49.3
1717	2014	Unintentional injuries	Alaska	379	55.0
1718	2014	Unintentional injuries	Arizona	3,322	47.0
1719	2014	Unintentional injuries	Arkansas	1,458	47.4
1720	2014	Unintentional injuries	California	11,804	29.2
...	...	...	...	...	...
5715	2008	Kidney disease	Virginia	1,537	20.5
5716	2008	Kidney disease	Washington	471	7.1
5717	2008	Kidney disease	West Virginia	522	23.0
5718	2008	Kidney disease	Wisconsin	1,007	15.5
5719	2008	Kidney disease	Wyoming	56	10.8

4004 rows × 5 columns

Population Averages

First we need the average population of New York City between the years 2008-2014. We have to use two datasets from the US Census website. Sources: https://www.census.gov/programs-surveys/popest/data/tables.html

NYC population

Because our dataset is split between 2 decades, with 2008 and 2009 occurring during 2000-2010, and 2010-2014 occurring during 2010-2020, we need to merge this data to form our own dataframe for our analysis.

In [13]:

```
#2008-2010 nyc population sum
nyc_pop_00_10 = pd.read_csv("nyc_and_state_pop_00_10.csv", encoding='la
tin-1')
idx = nyc_pop_00_10.loc[nyc_pop_00_10["NAME"] == "New York city"].index
[0]
nyc_avg_population = nyc_pop_00_10["POPESTIMATE2008"][idx] + nyc_pop_00
_10["POPESTIMATE2009"][idx] + nyc_pop_00_10["CENSUS2010POP"][idx]
```

In [14]:

```
#2011 - 2014 population sum
nyc_pop_10_18 = pd.read_csv("nyc_and_city_pop_10_18.csv")
avg = int(nyc_pop_10_18["respop72011"][1]) + int(nyc_pop_10_18["respop7
2012"][1]) + int(nyc_pop_10_18["respop72013"][1]) + int(nyc_pop_10_18[
"respop72014"][1])
nyc_avg_population += avg
nyc_avg_population = round(nyc_avg_population/7)

#avg population 2008-2014
print("Average NYC population in the year 2008-2014: ", nyc_avg_populat
```

```
ion)
nyc_pop_10_18.head()
```

```
Average NYC population in the year 2008-2014:  8261718.0
```

Out[14]:

	GEO.id	GEO.id2	GEO.display-label	GC_RANK.target-geo-id	GC_RANK.target-geo-id2	GC_RANK.rank-label	GC
0	Id	Id2	Geography	Target Geo Id	Target Geo Id2	Rank	
1	0100000US	NaN	United States	1620000US3651000	3651000	1	Uni Yo
2	0100000US	NaN	United States	1620000US0644000	644000	2	Ur
3	0100000US	NaN	United States	1620000US1714000	1714000	3	Ch
4	0100000US	NaN	United States	1620000US4835000	4835000	4	Hc

US Population

In [15]:

```
#2008 - 2010 national population sum
us_pop_00_10 = pd.read_csv("us_pop_00_10.csv")

#Census norm is to use month of July
us_pop_00_10 = us_pop_00_10.loc[us_pop_00_10["MONTH"] == 6]
us_pop_00_10 = us_pop_00_10.iloc[-2:]
national_avg_population = us_pop_00_10["TOT_POP"][98] + us_pop_00_10["T
OT_POP"][110]
us_pop_00_10
```

Out[15]:

	YEAR	MONTH	TOT_POP

	YEAR	MONTH	TOT_POP
98	2008	6	303847001
110	2009	6	306541114

In [16]:
```
#2010 - 2014 national population sum
us_pop_10_19 = pd.read_csv("us_and_state_pop_10_19.csv")
us_pop_10_19.drop([1,2,3,4,13,56],inplace=True)
add = us_pop_10_19["CENSUS2010POP"][0] + us_pop_10_19["POPESTIMATE2011"
][0] + us_pop_10_19["POPESTIMATE2012"][0] + us_pop_10_19["POPESTIMATE20
13"][0] + us_pop_10_19["POPESTIMATE2014"][0]
national_avg_population += add
national_avg_population = round(national_avg_population/7)

print("Average national population in the year 2008-2014: ", national_a
vg_population)
us_pop_10_19.head()
```

```
Average national population in the year 2008-2014:  311259463.0
```

Out[16]:

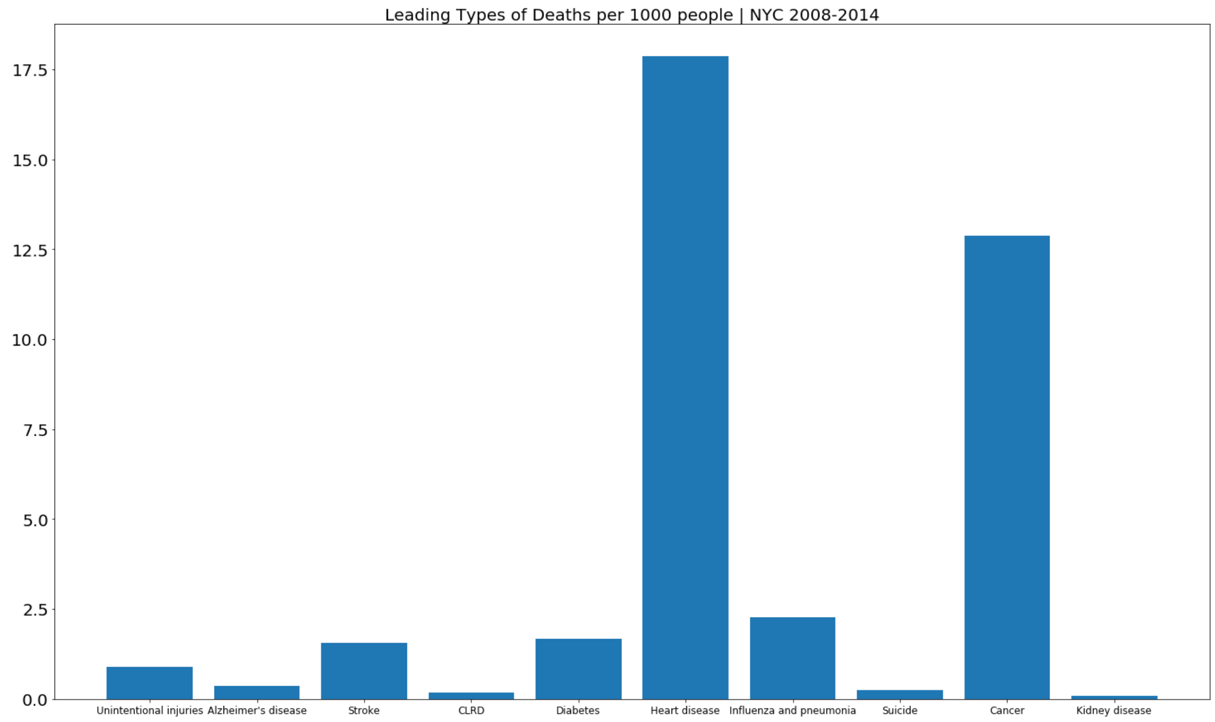
	SUMLEV	REGION	DIVISION	STATE	NAME	CENSUS2010POP	ESTIMATESBASE2010	POPI
0	10	0	0	0	United States	308745538	308758105	
5	40	3	6	1	Alabama	4779736	4780125	
6	40	4	9	2	Alaska	710231	710249	
7	40	4	8	4	Arizona	6392017	6392288	
8	40	3	7	5	Arkansas	2915918	2916031	

5 rows × 151 columns

Visualization of Leading Deaths

Preparation of NYC Dataset

In [17]:
```
#Get per 1000 quotient
nyc_per_1000_quotient = nyc_avg_population / 1000

#use us data to make dict so we can combine later
nyc_causes = dict(zip(us["Cause Name"],[0]*len(nyc)))
del nyc_causes["All causes"]

#put leading causes in dict
for index, row in nyc.iterrows():
    nyc_causes[(nyc["Leading Cause"][index])] += nyc["Deaths"][index]

#dividing to get per 1000 ratio
for key in nyc_causes.keys():
    nyc_causes[key] = nyc_causes[key]/nyc_per_1000_quotient

#plot
figure, ax = plt.subplots(figsize=(25,15))
mpl.pyplot.bar(x=nyc_causes.keys(),height=nyc_causes.values())
ax.set_title("Leading Types of Deaths per 1000 people | NYC 2008-2014",
 size = 20)
ax.tick_params(axis='y', which='major', labelsize=20)
ax.tick_params(axis='x', which='major', labelsize=12)
```

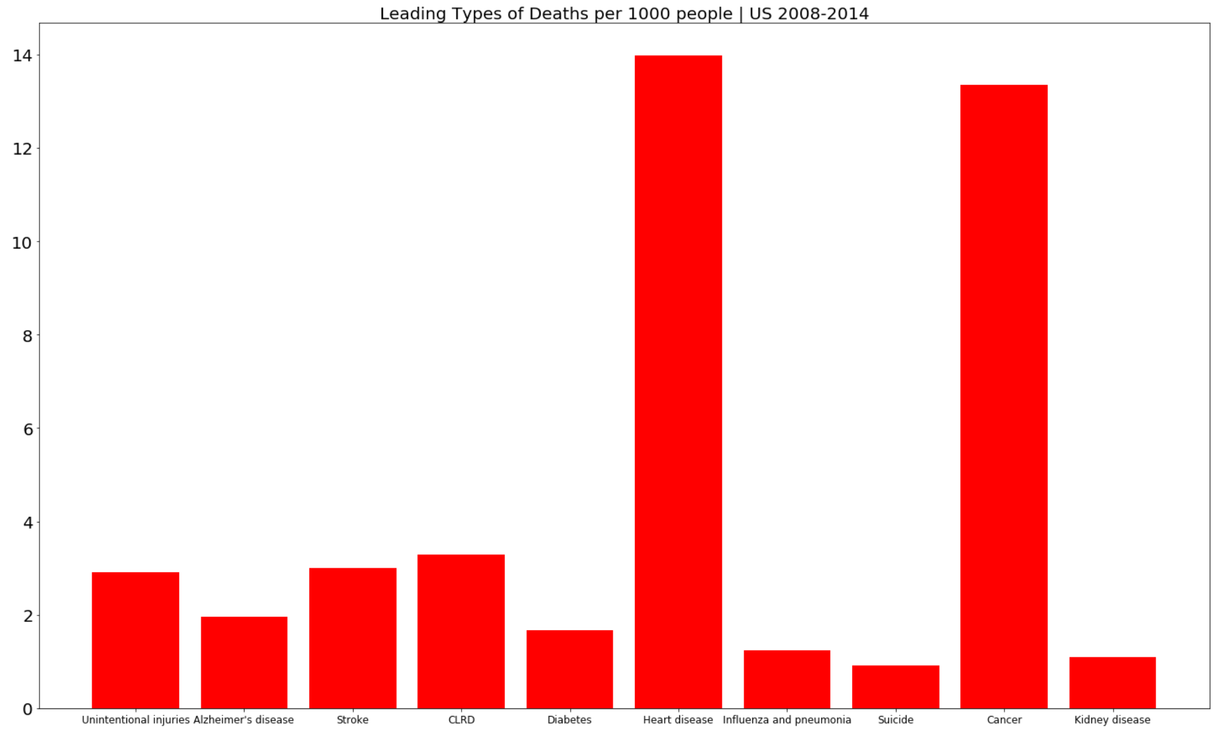


Preparation of US Dataset

In [18]:
```
#get rid of comma in us data
us["Deaths"] = us["Deaths"].str.replace(",","").astype(float)

#create quotient for per 1000 use. subtract nyc population
us_pop_minus_nyc = national_avg_population - nyc_avg_population
us_per_1000_quotient = us_pop_minus_nyc/1000
```

In [19]:
```
#create dict of causes
us_causes = dict(zip(us["Cause Name"],[0]*len(us)))
del us_causes["All causes"]

#add data to dict
```

```
for index, row in us.iterrows():
    if (us["Cause Name"][index]) == "All causes" or (us["State"][index]
 == "United States"):
        continue
    us_causes[(us["Cause Name"][index])] += us["Deaths"][index]

#create per 1000 ratio
for key in us_causes.keys():
    us_causes[key] = us_causes[key]/ us_per_1000_quotient

#plot
figure, ax = plt.subplots(figsize=(25,15))
mpl.pyplot.bar(x=us_causes.keys(),height=us_causes.values(),color="r")
ax.set_title("Leading Types of Deaths per 1000 people | US 2008-2014",
size = 20)
ax.tick_params(axis='y', which='major', labelsize=20)
ax.tick_params(axis='x', which='major', labelsize=12)
```

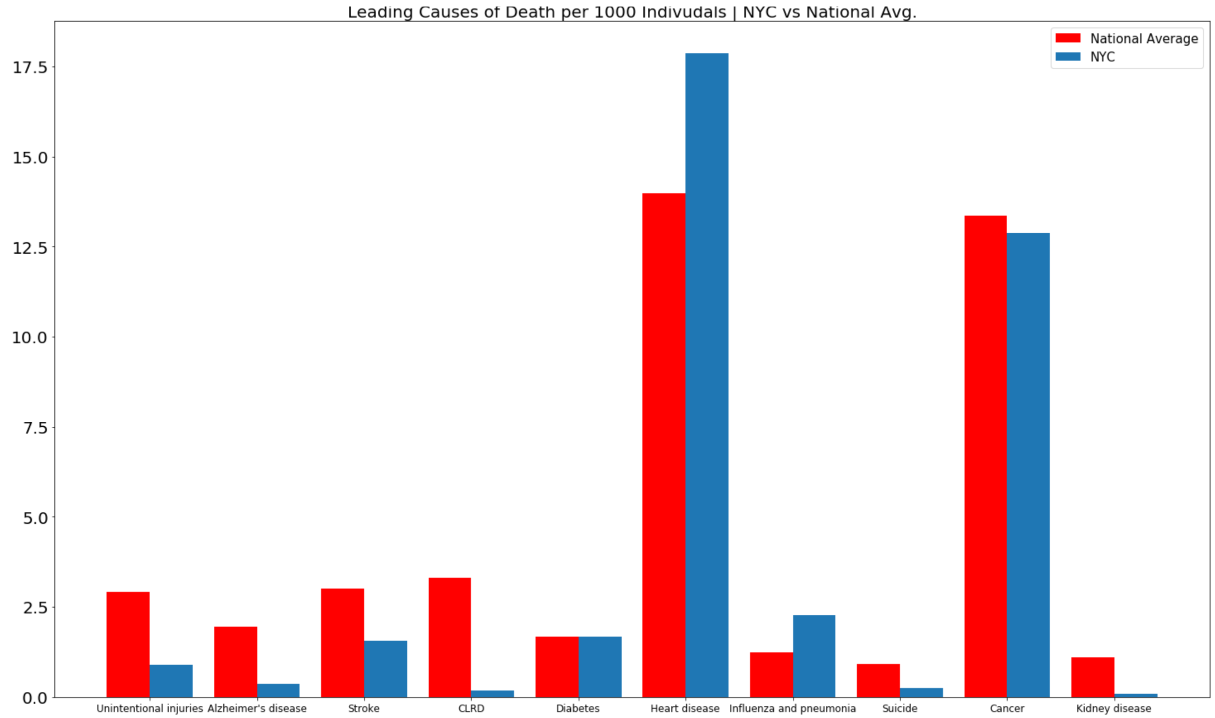


Combined Visualization

We have successfully created our own dataframe for our time range for both NYC and the US, now to visually compare the two, we will plot them on the same graph.

In [20]:
```
#plot on same figure
figure, ax = plt.subplots(figsize=(25,15))
N = 10
width = .4
ind = np.arange(N)
p1 = mpl.pyplot.bar(ind,us_causes.values(),width, color = 'r')
p2 = mpl.pyplot.bar(ind+width,nyc_causes.values(), width)
ax.legend((p1, p2), ('National Average', 'NYC'),fontsize=15)
labels = tuple(us_causes.keys())
ax.set_xticklabels((labels[0],labels[1],labels[2],labels[3], labels[4],labels[5],labels[6],labels[7],labels[8],labels[9]))
ax.set_xticks(ind + width / 2)
ax.tick_params(axis='y', which='major', labelsize=20)
ax.tick_params(axis='x', which='major', labelsize=12)
ax.set_title("Leading Causes of Death per 1000 Indivudals | NYC vs National Avg.", size = 20)
```

Out[20]:
```
Text(0.5, 1.0, 'Leading Causes of Death per 1000 Indivudals | NYC vs National Avg.')
```



Results

In [21]:

```
print("-------------------------------------\n")
print('NYC Heart Disease Deaths per 1000 people: ', nyc_causes["Heart d
isease"], "\n")
print('US Heart Disease Deaths per 1000 people: ', us_causes["Heart dis
ease"], "\n")
print("-------------------------------------\n")
print('NYC Influenza and Pneumonia Deaths per 1000 people: ', nyc_cause
s["Influenza and pneumonia"], "\n")
print('US Influenza and pneumonia Deaths per 1000 people: ', us_causes[
"Influenza and pneumonia"], "\n")
print("-------------------------------------\n")
print('NYC Accidental Deaths per 1000 people: ', nyc_causes["Unintentio
nal injuries"], "\n")
```

```
print('US Accidental Deaths per 1000 people: ', us_causes["Unintentional injuries"], "\n")
print("------------------------------------\n")
```

```
------------------------------------

NYC Heart Disease Deaths per 1000 people:  17.85960256692373

US Heart Disease Deaths per 1000 people:  13.979216247962505

------------------------------------

NYC Influenza and Pneumonia Deaths per 1000 people:  2.2607888577170026


US Influenza and pneumonia Deaths per 1000 people:  1.243378890493063

------------------------------------

NYC Accidental Deaths per 1000 people:  0.903807174246325

US Accidental Deaths per 1000 people:  2.909252674471224

------------------------------------
```

From our results, we see that the leading causes of deaths are comparable across the board, however there are 3 areas we would like to emphasize: heart disease, influenza, and unintentional injuries.

According to the data, New Yorkers are more likely to die from these first two causes than the rest of the country, and less likely to die from unintentional injuries. Heart disease has a significant increase in New York, the influenza/pneumonia death rate for NYC is almost double the rest of the country, and the rate at which New Yorkers die of unintentional injuries is less than half the national average.

Concluding this section of our analysis, we will further examine these three specific causes of death.

II. Analysis of Heart Disease, Influenza & Pneumonia, and Unintentional Injuries

1. Heart Disease

Pre-existing health conditions, genetics, lifestyle, etc. are all reasons why an individual may develop heart disease. However, according to the CDC there are 3 primary risk factors for Heart Disease: 1) smoking 2) high cholesterol 3) high blood pressure.

a. Risk Factors: Smoking

Sources:

https://www.cdc.gov/heartdisease/risk_factors.htm

https://www1.nyc.gov/assets/doh/downloads/pdf/data/macroscope-smoking-factsheet.pdf

https://www.cdc.gov/tobacco/data_statistics/fact_sheets/adult_data/cig_smoking/index.htm

According to the CDC, 13.7% of all adult americans smoke cigarettes. The New York City local government reports that 15.2% of adults in New York smoke cigarettes. While slightly above the national average, this would not explain the large jump in deaths from heart disease.

b) Risk Factors: High cholesterol

Sources: https://www.health.ny.gov/statistics/brfss/reports/docs/1510_brfss_high_cholesterol.pdf

According to the CDC and measure in 2011 and 2013 (relevant dates to our data sets), the difference between the number of individuals with high cholesterol nationwide and in New York City holds no significant difference. Nationwide, 38.4% of adults sampled had high cholesterol, and in New York City this number was 38.1%. So this clearly does not explain the jump in our data.

c) Risk Factors: High Blood Pressure

Sources:
https://www.health.ny.gov/statistics/brfss/reports/docs/1507_brfss_high_blood_pressure.pdf

According to the CDC, high blood pressure is not more prevelant in New York City when compared to the rest of the country. What this means, is that the 3 primary risk factors do not explain our jump in deaths attributed to heart disease.

Conclusion

Given this information about all three primary risk factors for heart disease, this leaves us with two possibilities:

1) the difference in death rates between the years 2008-2014 is simply statistical variance and is not significant.

2) The causal factor that pushed the heart disease death rate up is unknown. While, there may or may not be other signifcant causal risk factors in New York that have produced the effect we see in the data, we see it more worthwhile to pursuit the other trends in the data, and leave this open ended to our audience.

Why might New Yorkers be at more risk to heart disease, given the primary risk factors are all at or below the national average? Our intuition would say this is simply variance in the data, however there maybe something there to investigate further.For now, we will turn out analysis into another trend seen in the data: Influenza.

2. Influenza and Pneumonia

Based on our previous analysis, New York City's death rate for Influenza and Pneumonia was more than double the national average in the given time frame. This information is telling of the troubles to come in the age of COVID-19. We would like to explore why NYC may have a higher death rate of influenza and pneumonia, in hopes that it may shed some light on the current pandemic.

a. Testing Population Density Regression

First we want to examine population density and its role in the mortality rate of influenza. We will use the states to perform the test, however we will include New York City as an individual state as well. The goal of this test is to identify whether or not population density has an effect on the death rate of influenza, so it is ok to widen our scope statewide. Due to limited data, we will limit the breadth of the test to the 2010 census data.

Prepare and merge data into one dataframe

Get NYC death rate

In [22]:
```
# scatter plot
# x = state population density
# y = deaths per 1000 people from flu
nyc_per_1000_quotient
nat_popd = us.copy(deep=True)
nyc_popd = nyc.copy(deep=True)

nyc_popd = nyc_popd.loc[nyc_popd["Leading Cause"] == "Influenza and pne
umonia"]
nyc_death_rate = nyc_popd['Deaths'].sum()/nyc_per_1000_quotient
print("Death rate of Influenza in NYC: ", nyc_death_rate)
nyc_popd
```

```
Death rate of Influenza in NYC:  2.2607888577170026
```

Out[22]:

	Year	Leading Cause	Sex	Race Ethnicity	Deaths	Death Rate	Age Adjusted Death Rate
0	2010	Influenza and pneumonia	F	Hispanic	228.0	18.7	23.1
21	2009	Influenza and pneumonia	M	Hispanic	183.0	16.3	30.9
42	2009	Influenza and pneumonia	F	Black Non-Hispanic	281.0	26.8	24.5
71	2009	Influenza and pneumonia	M	White Non-Hispanic	555.0	41.3	34.3
83	2007	Influenza and pneumonia	F	Black Non-Hispanic	295.0	28.0	26.9
...	...	...	...	...	...	...	...
984	2012	Influenza and pneumonia	F	Black Non-Hispanic	295.0	28.2	24.1
987	2007	Influenza and pneumonia	M	Asian and Pacific Islander	66.0	13.6	25.7
1011	2010	Influenza and pneumonia	M	Asian and Pacific Islander	108.0	20.7	31.7
1031	2012	Influenza and pneumonia	F	Hispanic	209.0	16.9	19.6
1089	2012	Influenza and pneumonia	F	Not Stated/Unknown	6.0	0.0	0.0

96 rows × 7 columns

Prepare and merge state death/population data to our nationwide dataset

In [23]:

```
#drop DOC and UNITED STATES rows
us_per_1000_quotient
```

```
nat_popd = nat_popd.loc[nat_popd["Cause Name"] == "Influenza and pneumo
nia"]
not_states = nat_popd.loc[nat_popd["State"] == "District of Columbia"].
index
not_states = not_states.union(nat_popd.loc[nat_popd["State"] == "United
 States"].index)
nat_popd = nat_popd.drop(not_states)

#put states and total deaths in a dictionary
state_deaths = {}
for index, row in nat_popd.iterrows():
    try:
        state_deaths[nat_popd["State"][index]] += nat_popd["Deaths"][in
dex]
    except:
        state_deaths[nat_popd["State"][index]] = nat_popd["Deaths"][ind
ex]
```

In [24]:
```
#Get all the states in a dictionary with total populations from 2008-20
10

state_pops_00_10 = pd.read_csv("nyc_and_state_pop_00_10.csv",encoding=
'latin-1')
state_pops_00_10 = state_pops_00_10.drop(state_pops_00_10.loc[state_pop
s_00_10["NAME"]=="District of Columbia"].index)
states_population = {}
for index,row in state_pops_00_10.iterrows():
     if state_pops_00_10["NAME"][index] == state_pops_00_10["STNAME"][i
ndex]:
            states_population[state_pops_00_10["NAME"][index]] = state_
pops_00_10["POPESTIMATE2008"][index] + state_pops_00_10["POPESTIMATE200
9"][index] +state_pops_00_10["CENSUS2010POP"][index]
len(states_population.keys())
```

Out[24]: 50

In [25]:
```
##Get all the states in a dictionary with total populations from 2011-2
014
state_pops_10_19 = pd.read_csv("us_and_state_pop_10_19.csv")
```

```
state_pops_10_19

#get rid of extras
for index,row in state_pops_10_19.iterrows():
    if state_pops_10_19["NAME"][index] not in states_population.keys():
        state_pops_10_19.drop([index], inplace = True)

#add to our dict
for index,row in state_pops_10_19.iterrows():
    states_population[state_pops_10_19["NAME"][index]] += state_pops_10
_19["POPESTIMATE2011"][index] + state_pops_10_19["POPESTIMATE2012"][ind
ex] + state_pops_10_19["POPESTIMATE2013"][index] + state_pops_10_19["PO
PESTIMATE2014"][index]

#get avg population
for key in states_population.keys():
    states_population[key] = round(states_population[key]/7)
```

In [26]:

```
#get per 1000 death rates for each state. These are avg values for year
s 2008-2014

for key in state_deaths.keys():
    state_deaths[key] = state_deaths[key] / (states_population[key]/100
0)
state_deaths
```

Out[26]:

```
{'Alabama': 1.4117944627605559,
 'Alaska': 0.5714285714285714,
 'Arizona': 0.8975399973391377,
 'Arkansas': 1.7623788940534817,
 'California': 1.1541322846823119,
 'Colorado': 0.8472529542475589,
 'Connecticut': 1.2461243715942876,
 'Delaware': 1.0634171283990779,
 'Florida': 0.8972745018728858,
 'Georgia': 1.0521908082938978,
 'Hawaii': 1.7899275892929785,
 'Idaho': 0.9389873091378756,
 'Illinois': 1.3215314005219632,
 'Indiana': 1.2105206421180104,
```

```
 'Iowa': 1.5400055370985604,
 'Kansas': 1.5751870665616077,
 'Kentucky': 1.532035246901929,
 'Louisiana': 1.3312964585276361,
 'Maine': 1.3325818905808056,
 'Maryland': 1.2101984052766228,
 'Massachusetts': 1.5020294486695955,
 'Michigan': 1.2193424594100062,
 'Minnesota': 0.8794081009181126,
 'Mississippi': 1.5035353762941133,
 'Missouri': 1.5036368581172062,
 'Montana': 1.2143680176343872,
 'Nebraska': 1.2005611318333569,
 'Nevada': 1.3582572063905562,
 'New Hampshire': 1.0893913706586051,
 'New Jersey': 1.0023170918907234,
 'New Mexico': 1.1321058039549134,
 'New York': 1.6795959228529547,
 'North Carolina': 1.2979678586974428,
 'North Dakota': 1.4098417073110776,
 'Ohio': 1.333531073057469,
 'Oklahoma': 1.4575571416334157,
 'Oregon': 0.819872891252008,
 'Pennsylvania': 1.429410759094455,
 'Rhode Island': 1.360069350258641,
 'South Carolina': 1.1177742579476424,
 'South Dakota': 1.4657757144746566,
 'Tennessee': 1.6015123953495969,
 'Texas': 0.8888148524110122,
 'Utah': 0.8893983150941971,
 'Vermont': 0.7768418024008568,
 'Virginia': 1.1653041568738787,
 'Washington': 0.7390895139253651,
 'West Virginia': 1.7076388341164739,
 'Wisconsin': 1.2466809400058476,
 'Wyoming': 1.418379809029061}
```

In [27]:
```
#fix death rate
```

```
#add new york to dataframe
#drop year column, using the averge population year not needed

nat_popd.drop(columns=["Year"],inplace=True)
states = list(state_deaths.keys())

#Change state deaths column to 1000 death rate instead of raw num of de
aths
for index,row in nat_popd.iterrows():
    if nat_popd["State"][index] in states:
        nat_popd["Deaths"][index] = state_deaths[nat_popd["State"][inde
x]]
        states.remove(nat_popd["State"][index])
    else:
        nat_popd.drop([index], inplace=True)

#add nyc to dataframe
df_nyc = pd.DataFrame([['Influenza and pneumonia', 'New York City',nyc_
causes["Influenza and pneumonia"], np.nan]],columns=["Cause Name", "Sta
te", "Deaths", "Age-adjusted Death Rate"])
nat_popd = nat_popd.append(df_nyc)
nat_popd.rename(columns={"Deaths":"Death Rate"},inplace=True)

nat_popd
```

```
/opt/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:11: Se
ttingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

Out[27]:

	Cause Name	State	Death Rate	Age-adjusted Death Rate
2080	Influenza and pneumonia	Alabama	1.411794	18.8
2081	Influenza and pneumonia	Alaska	0.571429	14.1

2082	Influenza and pneumonia	Arizona	0.897540	10.0

	Cause Name	State	Death Rate	Age-adjusted Death Rate
2083	Influenza and pneumonia	Arkansas	1.762379	20.7
2084	Influenza and pneumonia	California	1.154132	14.7
2085	Influenza and pneumonia	Colorado	0.847253	13.3
2086	Influenza and pneumonia	Connecticut	1.246124	13.3
2087	Influenza and pneumonia	Delaware	1.063417	13.8
2089	Influenza and pneumonia	Florida	0.897275	9.6
2090	Influenza and pneumonia	Georgia	1.052191	16.2
2091	Influenza and pneumonia	Hawaii	1.789928	22.6
2092	Influenza and pneumonia	Idaho	0.938987	11.3
2093	Influenza and pneumonia	Illinois	1.321531	16.8
2094	Influenza and pneumonia	Indiana	1.210521	14.3
2095	Influenza and pneumonia	Iowa	1.540006	13.7
2096	Influenza and pneumonia	Kansas	1.575187	18.2
2097	Influenza and pneumonia	Kentucky	1.532035	20.8
2098	Influenza and pneumonia	Louisiana	1.331296	17.5
2099	Influenza and pneumonia	Maine	1.332582	13.7
2100	Influenza and pneumonia	Maryland	1.210198	15.6
2101	Influenza and pneumonia	Massachusetts	1.502029	15.8
2102	Influenza and pneumonia	Michigan	1.219342	15.5
2103	Influenza and pneumonia	Minnesota	0.879408	9.8
2104	Influenza and pneumonia	Mississippi	1.503535	23.5
2105	Influenza and pneumonia	Missouri	1.503637	18.1
2106	Influenza and pneumonia	Montana	1.214368	13.7
2107	Influenza and pneumonia	Nebraska	1.200561	15.1

	Cause Name	State	Death Rate	Age-adjusted Death Rate
2107	Influenza and pneumonia	Nebraska	1.200561	15.1
2108	Influenza and pneumonia	Nevada	1.358257	23.8
2109	Influenza and pneumonia	New Hampshire	1.089391	11.5
2110	Influenza and pneumonia	New Jersey	1.002317	11.3
2111	Influenza and pneumonia	New Mexico	1.132106	16.1
2112	Influenza and pneumonia	New York	1.679596	19.5
2113	Influenza and pneumonia	North Carolina	1.297968	17.2
2114	Influenza and pneumonia	North Dakota	1.409842	18.5
2115	Influenza and pneumonia	Ohio	1.333531	16.9
2116	Influenza and pneumonia	Oklahoma	1.457557	16.8
2117	Influenza and pneumonia	Oregon	0.819873	9.1
2118	Influenza and pneumonia	Pennsylvania	1.429411	14.2
2119	Influenza and pneumonia	Rhode Island	1.360069	11.7
2120	Influenza and pneumonia	South Carolina	1.117774	13.9
2121	Influenza and pneumonia	South Dakota	1.465776	16.2
2122	Influenza and pneumonia	Tennessee	1.601512	22.1
2123	Influenza and pneumonia	Texas	0.888815	14.2
2125	Influenza and pneumonia	Utah	0.889398	16.2
2126	Influenza and pneumonia	Vermont	0.776842	9.3
2127	Influenza and pneumonia	Virginia	1.165304	17.1
2128	Influenza and pneumonia	Washington	0.739090	9.4
2129	Influenza and pneumonia	West Virginia	1.707639	19.6
2130	Influenza and pneumonia	Wisconsin	1.246681	13.8
2131	Influenza and pneumonia	Wyoming	1.418380	18.1
0	Influenza and pneumonia	New York City	2.260789	NaN

Load in and merge population density data.

Because population density data is difficult to find and aggregate, we will be using the data from the 2010 census.

In [28]:
```
#DENSITY EXPRESSED AS PEOPLE PER SQUARE MILE.
pop_density = pd.read_csv("pop_density.csv")
cols = list(pop_density.columns)

#rename our messed up column names
for k in range(len(cols)):
    pop_density.rename(columns = {cols[k]:pop_density[cols[k]][2]}, inp
lace=True)

#drop descriptive / DOC and United States  rows
pop_density.drop([0,1,2,3,12,55],inplace=True)

#get rid of commas in values
pop_density["2010_DENSITY"] = pop_density["2010_DENSITY"].str.replace(
",","").astype(float)

pop_density_dic = {}
for index, row in pop_density.iterrows():
    pop_density_dic[pop_density["STATE_OR_REGION"][index]] = float(pop_
density["2010_DENSITY"][index])

pop_density_dic
```

Out[28]:
```
{'Alabama': 94.4,
 'Alaska': 1.2,
 'Arizona': 56.3,
 'Arkansas': 56.0,
 'California': 239.1,
 'Colorado': 48.5,
 'Connecticut': 738.1,
 'Delaware': 460.8,
 'Florida': 350.6,
 'Georgia': 168.4
```

```
 'Georgia': 168.4,
 'Hawaii': 211.8,
 'Idaho': 19.0,
 'Illinois': 231.1,
 'Indiana': 181.0,
 'Iowa': 54.5,
 'Kansas': 34.9,
 'Kentucky': 109.9,
 'Louisiana': 104.9,
 'Maine': 43.1,
 'Maryland': 594.8,
 'Massachusetts': 839.4,
 'Michigan': 174.8,
 'Minnesota': 66.6,
 'Mississippi': 63.2,
 'Missouri': 87.1,
 'Montana': 6.8,
 'Nebraska': 23.8,
 'Nevada': 24.6,
 'New Hampshire': 147.0,
 'New Jersey': 1195.5,
 'New Mexico': 17.0,
 'New York': 411.2,
 'North Carolina': 196.1,
 'North Dakota': 9.7,
 'Ohio': 282.3,
 'Oklahoma': 54.7,
 'Oregon': 39.9,
 'Pennsylvania': 283.9,
 'Rhode Island': 1018.1,
 'South Carolina': 153.9,
 'South Dakota': 10.7,
 'Tennessee': 153.9,
 'Texas': 96.3,
 'Utah': 33.6,
 'Vermont': 67.9,
 'Virginia': 202.6,
 'Washington': 101.2,
 'West Virginia': 77.1,
 'Wisconsin': 105.0,
```

```
 'Wyoming': 5.8}
```

In [29]:
```
#merge our data sets
nat_popd["Pop Density"] = np.nan
for index,row in nat_popd.iterrows():
    if nat_popd["State"][index] == "New York City":
        pass
        nat_popd["Pop Density"][index] = 27011.8 #hard code nyc 2010 po
p density into our dataset
    else:
        nat_popd["Pop Density"][index] = pop_density_dic[nat_popd["Stat
e"][index]]

nat_popd.columns
```

```
/opt/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:8: Set
tingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

/opt/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:6: Set
tingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

Out[29]:
```
Index(['Cause Name', 'State', 'Death Rate', 'Age-adjusted Death Rate',
       'Pop Density'],
      dtype='object')
```

i. Population Density Regression Test

We will be regressing population density, so our y will be the influenza death rate and x will be the population density.

In [30]:
```
nat_popd_reg = nat_popd.copy(deep=True)
nat_popd_reg.columns = nat_popd_reg.columns.str.strip().str.lower().str
.replace(" ", "_").str.replace("-", "_")
list(nat_popd_reg.columns.values)
```

Out[30]:
```
['cause_name', 'state', 'death_rate', 'age_adjusted_death_rate', 'pop_d
ensity']
```

In [31]:
```
reg = smf.ols("death_rate ~ pop_density", data = nat_popd_reg).fit()
print(reg.summary())
```

```
                            OLS Regression Results

========================================================================
=======
Dep. Variable:             death_rate   R-squared:
  0.203
Model:                            OLS   Adj. R-squared:
  0.187
Method:                 Least Squares   F-statistic:
  12.48
Date:                Wed, 13 May 2020   Prob (F-statistic):
0.000908
Time:                        20:04:28   Log-Likelihood:
-7.6312
No. Observations:                  51   AIC:
  19.26
Df Residuals:                      49   BIC:
  23.13
Df Model:                           1

Covariance Type:            nonrobust
```

```
==============================================================================
========
                 coef    std err          t      P>|t|      [0.025
  0.975]
------------------------------------------------------------------------------
--------
Intercept       1.2345      0.041     30.189      0.000       1.152
   1.317
pop_density  3.805e-05   1.08e-05      3.533      0.001    1.64e-05
5.97e-05
==============================================================================
=======
Omnibus:                        1.073   Durbin-Watson:
  2.032
Prob(Omnibus):                  0.585   Jarque-Bera (JB):
  1.012
Skew:                          -0.168   Prob(JB):
  0.603
Kurtosis:                       2.397   Cond. No.
3.87e+03
==============================================================================
=======

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 3.87e+03. This might indicate that t
here are
strong multicollinearity or other numerical problems.
```

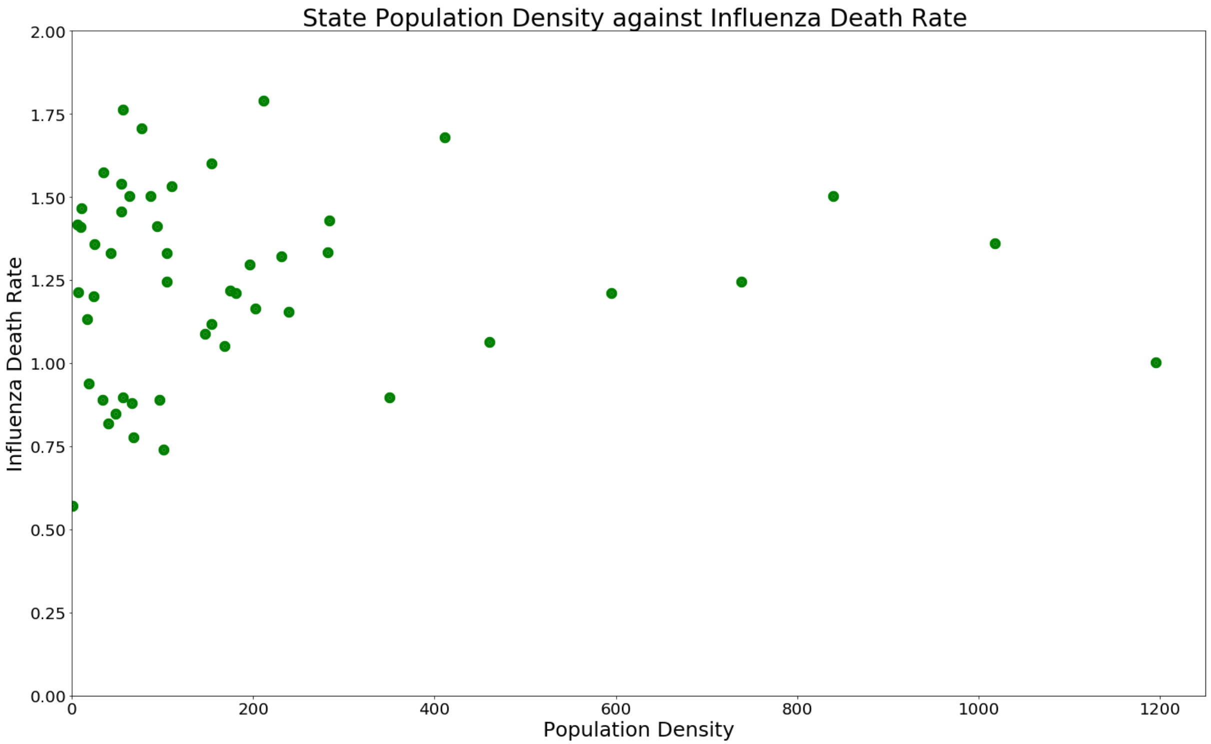
ii. Visualization of Population Density Against Influenza Death Rate

In [32]:

```
import itertools
import matplotlib
#nat_popd.drop([0],inplace=True)
figure, ax = plt.subplots(figsize=(25,15))
```

```
nat_popd.plot.scatter(x="Pop Density", y = "Death Rate",ax=ax,c='g',lin
ewidths=9)
ax.set_title("State Population Density against Influenza Death Rate ",f
ontsize=30)
ax.set_ylabel("Influenza Death Rate", size = 25)
ax.set_xlabel("Population Density", size = 25)
ax.tick_params(axis='y', which='major', labelsize=20)
ax.tick_params(axis='x', which='major', labelsize=20)
ax.set_xlim(0,1250)
ax.set_ylim(0,2)
```

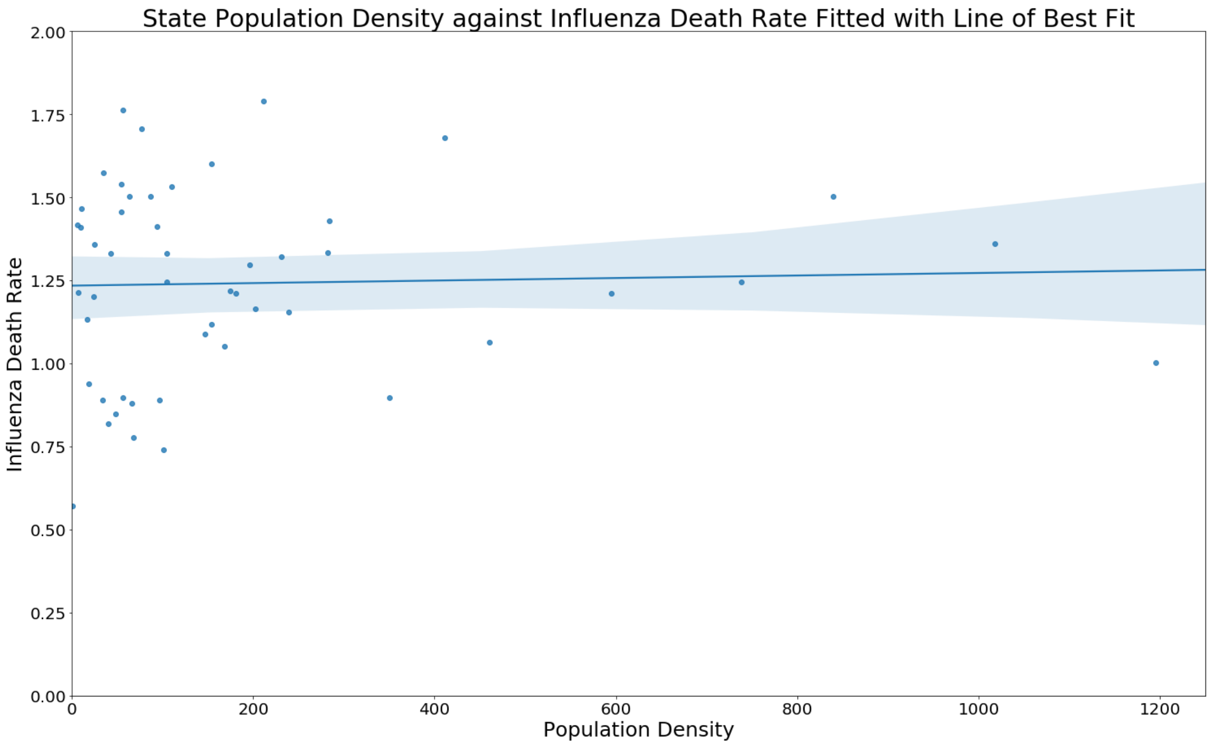
Out[32]: (0, 2)



In [33]:
```
figure, ax = plt.subplots(figsize=(25,15))
ax = sb.regplot(x="Pop Density", y="Death Rate", data=nat_popd)
ax.tick_params(axis='y', which='major', labelsize=20)
ax.tick_params(axis='x', which='major', labelsize=20)
```

```
ax.set_ylabel("Influenza Death Rate", size = 25)
ax.set_xlabel("Population Density", size = 25)
ax.set_title("State Population Density against Influenza Death Rate Fit
ted with Line of Best Fit",fontsize=30)
ax.set_xlim(0,1250)
ax.set_ylim(0,2)
```

Out[33]: (0, 2)



iii. Conclusion

Based on our linear regression test, we can observe from the p-value that our results hold some weight, but do not tel us much. The density of a population does affect the influenza death rate, however, since our R-squared value is relatively low, we know that this may not be a deterministic factor. This is also logical, although a slight trend can be seen in the graphs above, the margin of error is high, and the correlation is very low. At this point, we are convinced that there are potentially other factors that lead to a high infuenza death rate.

From here, we would like to run another regression on the number of hospitals and the death rate of influenza. Once we have completed further analysis on this, we are curious if our results transer to the death rates of COVID-19 as well, as both death rates are viral.

b. Urgent Center Units per Capita Regression testing

sources:
https://hifld-geoplatform.opendata.arcgis.com/datasets/urgent-care-facilities
https://nyshealthfoundation.org/wp-content/uploads/2017/11/united-hospital-fund-convenient-care-report.pdf

In [34]:
```
#dictionary of abbreviations for all 52 regions included in the dataset
us_state_abbrev = {
    'Alabama': 'AL',
    'Alaska': 'AK',
    'Arizona': 'AZ',
    'Arkansas': 'AR',
    'California': 'CA',
    'Colorado': 'CO',
    'Connecticut': 'CT',
    'Delaware': 'DE',
    'District of Columbia': 'DC',
    'Florida': 'FL',
    'Georgia': 'GA',
    'Hawaii': 'HI',
    'Idaho': 'ID',
    'Illinois': 'IL',
    'Indiana': 'IN',
    'Iowa': 'IA',
    'Kansas': 'KS',
    'Kentucky': 'KY',
    'Louisiana': 'LA',
    'Maine': 'ME',
```

```
    'Maryland': 'MD',
    'Massachusetts': 'MA',
    'Michigan': 'MI',
    'Minnesota': 'MN',
    'Mississippi': 'MS',
    'Missouri': 'MO',
    'Montana': 'MT',
    'Nebraska': 'NE',
    'Nevada': 'NV',
    'New Hampshire': 'NH',
    'New Jersey': 'NJ',
    'New Mexico': 'NM',
    'New York': 'NY',
    'North Carolina': 'NC',
    'North Dakota': 'ND',
    'Ohio': 'OH',
    'Oklahoma': 'OK',
    'Oregon': 'OR',
    'Pennsylvania': 'PA',
    'Puerto Rico': 'PR',
    'Rhode Island': 'RI',
    'South Carolina': 'SC',
    'South Dakota': 'SD',
    'Tennessee': 'TN',
    'Texas': 'TX',
    'United States': 'US',
    'Utah': 'UT',
    'Vermont': 'VT',
    'Virginia': 'VA',
    'Washington': 'WA',
    'West Virginia': 'WV',
    'Wisconsin': 'WI',
    'Wyoming': 'WY'
}
```

In [35]:

```
urgent_centers = pd.read_csv("Urgent_Care_Facilities.csv")
#load in urgent care units
uc_states = urgent_centers["STATE"].unique()
states = nat_popd["State"].unique()
```

```
state_units = []

#get the amount of urgent care units per state
for state in states:
    if state == "New York City":
        continue
    num_units = round(len(urgent_centers.loc[urgent_centers["STATE"] ==
 us_state_abbrev[state]]) / (states_population[state]/100000),2)
    state_units.append(num_units)

#hardcode nyc into df
state_units.append(round(103 / (8261718.0/100000),2)) #number of units
 in nyc
nat_popd["Urgent Care Units"] = state_units
nat_popd.head()
```

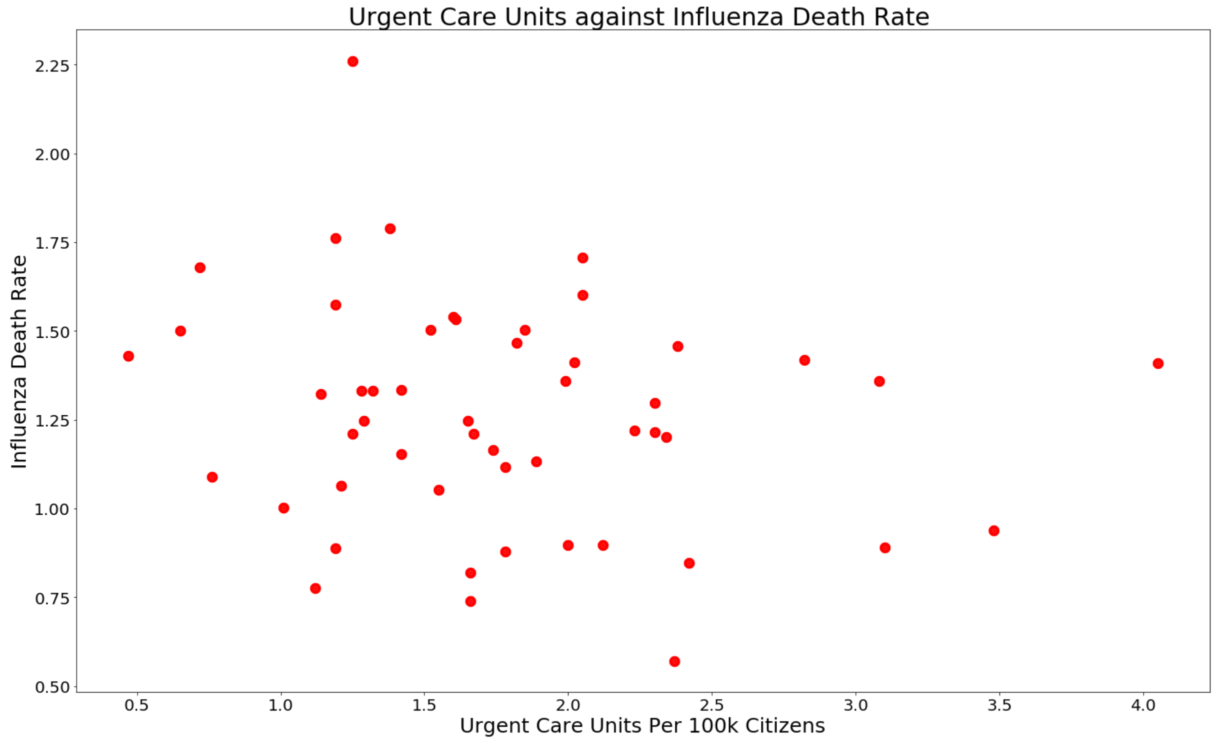
Out[35]:

	Cause Name	State	Death Rate	Age-adjusted Death Rate	Pop Density	Urgent Care Units
2080	Influenza and pneumonia	Alabama	1.411794	18.8	94.4	2.02
2081	Influenza and pneumonia	Alaska	0.571429	14.1	1.2	2.37
2082	Influenza and pneumonia	Arizona	0.897540	10.0	56.3	2.00
2083	Influenza and pneumonia	Arkansas	1.762379	20.7	56.0	1.19
2084	Influenza and pneumonia	California	1.154132	14.7	239.1	1.42

In [36]:

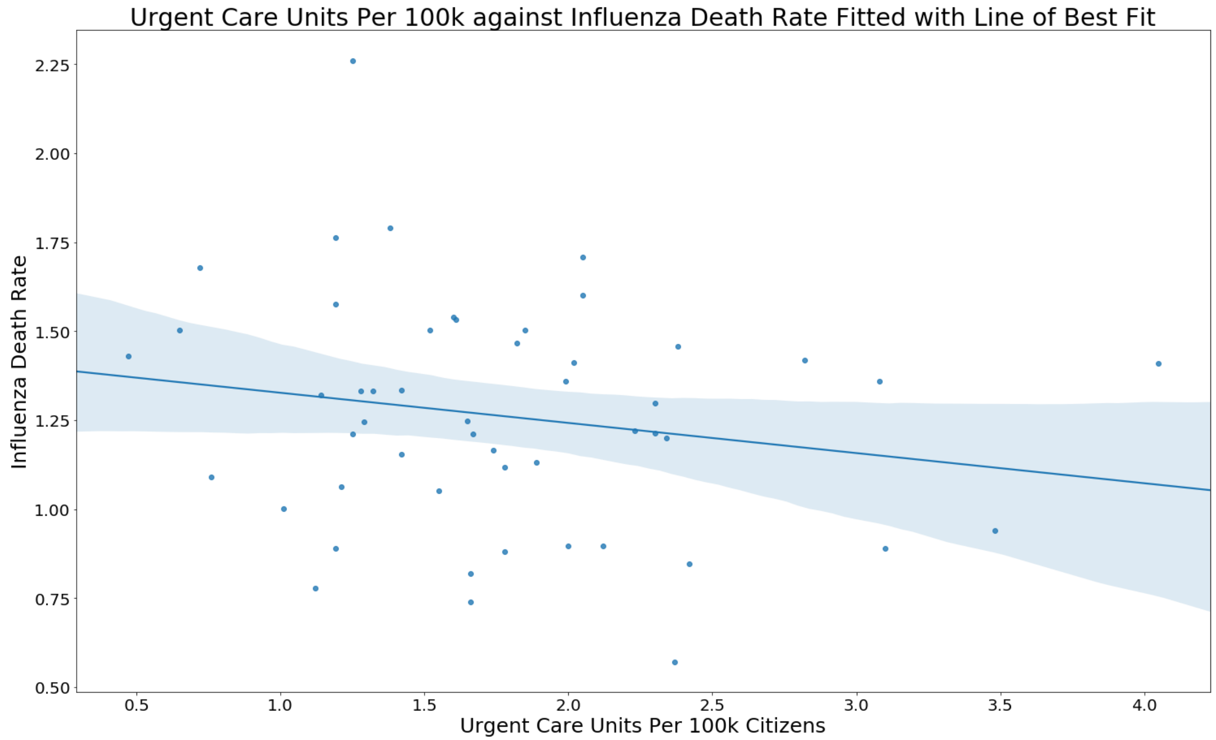
```
figure, ax = plt.subplots(figsize=(25,15))
nat_popd.plot.scatter(x="Urgent Care Units", y = "Death Rate",ax=ax,c=
'r',linewidths=9)
ax.set_title("Urgent Care Units against Influenza Death Rate ",fontsize
=30)
ax.set_ylabel("Influenza Death Rate", size = 25)
ax.set_xlabel("Urgent Care Units Per 100k Citizens", size = 25)
```

```
ax.tick_params(axis='y', which='major', labelsize=20)
ax.tick_params(axis='x', which='major', labelsize=20)
```



In [37]:
```
figure, ax = plt.subplots(figsize=(25,15))
ax = sb.regplot(x="Urgent Care Units", y="Death Rate", data=nat_popd)
ax.tick_params(axis='y', which='major', labelsize=20)
ax.tick_params(axis='x', which='major', labelsize=20)
ax.set_ylabel("Influenza Death Rate", size = 25)
ax.set_xlabel("Urgent Care Units Per 100k Citizens", size = 25)
ax.set_title("Urgent Care Units Per 100k against Influenza Death Rate F
itted with Line of Best Fit",fontsize=30)
```

Out[37]:
```
Text(0.5, 1.0, 'Urgent Care Units Per 100k against Influenza Death Rate
Fitted with Line of Best Fit')
```



Urgent Care Units Regression

In [38]:
```
nat_popd_reg_uc = nat_popd.copy(deep=True)
nat_popd_reg_uc.columns = nat_popd_reg_uc.columns.str.strip().str.lower
().str.replace(" ", "_").str.replace("-", "_")
reg = smf.ols("death_rate ~ urgent_care_units", data = nat_popd_reg_uc)
.fit()
print(reg.summary())
```

```
                            OLS Regression Results

==============================================================================
=======
Dep. Variable:             death_rate   R-squared:
  0.036
Model:                            OLS   Adj. R-squared:
```

```
Model:                            OLS   Adj. R-squared:
  0.016
Method:                 Least Squares   F-statistic:
  1.808
Date:                Wed, 13 May 2020   Prob (F-statistic):
  0.185
Time:                        20:04:31   Log-Likelihood:
-12.493
No. Observations:                  51   AIC:
  28.99
Df Residuals:                      49   BIC:
  32.85
Df Model:                           1

Covariance Type:            nonrobust

======================================================================
==============
                        coef    std err          t      P>|t|      [0.0
25      0.975]
----------------------------------------------------------------------
--------------
Intercept             1.4117      0.120     11.781      0.000       1.1
71       1.652
urgent_care_units    -0.0847      0.063     -1.345      0.185      -0.2
11       0.042
======================================================================
=======
Omnibus:                        1.664   Durbin-Watson:
  1.733
Prob(Omnibus):                  0.435   Jarque-Bera (JB):
  0.918
Skew:                           0.281   Prob(JB):
  0.632
Kurtosis:                       3.342   Cond. No.
   6.43
======================================================================
=======

Warnings:
```

```
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

We can see from the regression test that while there is some correlation between the number of urgent care units and influenza dates, it is not causal with a 95% confidence interval. This implies there are other outside factors influencing the influenza death rate.

c. Hospitals per Capita Regression testing

source:
https://www.ahd.com/state_statistics.html
https://www.beckershospitalreview.com/lists/62-acute-care-hospitals-in-new-york-city.html nyc hospitals

This dataset available for hospitals per state on the American Hospital Directory pulls data from each states individual webpage, so we will have to webscrape the table, since no csv is offered.

Webscrape the data

In [39]:

```
import requests
from lxml import html
```

PLEASE NOTE: for the below cell to work, you may have to open the url in another tab and enter a captcha for it to work. url = https://www.ahd.com/state_statistics.html

In [40]:

```
#You might have to go to this website and first enter a captcha for thi
s to work

url = "https://www.ahd.com/state_statistics.html"
page = requests.get(url)
```

```python
#Store the contents of the website under doc
doc = html.fromstring(page.content)
#Parse data that are stored between <tr>..</tr> of HTML
tr_elements = doc.xpath('//tr',remove_blank_text=True)

#get rid of wrong table
tr_elements = tr_elements[1:58]

#get the columns from the header
hosp_cols = []
for i in tr_elements[0]:
    hosp_cols.append((i.text_content(),[]))

#extract values from the table
for row in tr_elements[1:]:
    col_idx = 0
    #for each column
    for col_value in row.iterchildren():
        hosp_cols[col_idx][1].append(col_value.text_content())
        col_idx += 1

#create dataframe
hosp_cols_dic = {column:value for (column,value) in hosp_cols}
hospitals = pd.DataFrame(hosp_cols_dic)
hospitals.head()
```

Out[40]:

	State	NumberHospitals	StaffedBeds	TotalDischarges	PatientDays	Gross PatientRevenue ($000)
0	AK - Alaska	10	1,235	45,209	243,272	$5,374,320
1	AL - Alabama	89	15,330	592,368	2,818,440	$60,726,101
2	AR - Arkansas	52	7,873	315,200	1,385,087	$27,777,922
3	AS - American Samoa	1	0	0	0	$0
4	AZ - Arizona	73	13,416	610,133	2,660,941	$79,447,094

```
In [41]: #get state in correct format
hospitals["State"] = hospitals['State'].str[5:]

# sort the states into alphabetical order so we can merge and drop nons
tates (american samoa, PR, etc)
hospitals.sort_values("State",inplace=True)
for index,row in hospitals.iterrows():
    if hospitals["State"][index] not in states:
        hospitals.drop(index, inplace=True)

#reset the index
hospitals.reset_index(drop=True, inplace=True)
hospitals.head(10)

#hardcode nyc row
hospitals = hospitals.append({"State":"New York City", "NumberHospital
s":62, "StaffedBeds":0, "TotalDischarges":0, "PatientDays":0, "Gross Pa
tientRevenue ($000)":0},ignore_index=True)
hospitals = hospitals.replace(np.nan,0)
hospitals.head()
```

Out[41]:

	State	NumberHospitals	StaffedBeds	TotalDischarges	PatientDays	Gross PatientRevenue ($000)
0	Alabama	89	15,330	592,368	2,818,440	$60,726,101
1	Alaska	10	1,235	45,209	243,272	$5,374,320
2	Arizona	73	13,416	610,133	2,660,941	$79,447,094
3	Arkansas	52	7,873	315,200	1,385,087	$27,777,922
4	California	343	74,624	3,084,295	14,352,052	$484,959,610

Merge the data

```
In [42]: main_data = nat_popd.copy(deep=True)
main_data = main_data.merge(hospitals)
```

```
main_data.head()
```

Out[42]:

	Cause Name	State	Death Rate	Age-adjusted Death Rate	Pop Density	Urgent Care Units	NumberHospitals	StaffedBeds	Tota
0	Influenza and pneumonia	Alabama	1.411794	18.8	94.4	2.02	89	15,330	
1	Influenza and pneumonia	Alaska	0.571429	14.1	1.2	2.37	10	1,235	
2	Influenza and pneumonia	Arizona	0.897540	10.0	56.3	2.00	73	13,416	
3	Influenza and pneumonia	Arkansas	1.762379	20.7	56.0	1.19	52	7,873	
4	Influenza and pneumonia	California	1.154132	14.7	239.1	1.42	343	74,624	

In [43]:

```
#get the amount of hospitals per 100k citizens
for index,row in main_data.iterrows():
    if main_data["State"][index] == "New York City":
        continue
    main_data["NumberHospitals"][index] = float(main_data["NumberHospit
als"][index]) / round((states_population[main_data["State"][index]]/100
000),2)

#hardcode nyc into df
main_data["NumberHospitals"][50] = float(round(62 / (8261718.0/100000),
2)) #number of units in

#change hospital rows ot float
main_data["NumberHospitals"] = main_data["NumberHospitals"].astype(floa
```

```
t)
main_data.head()
```

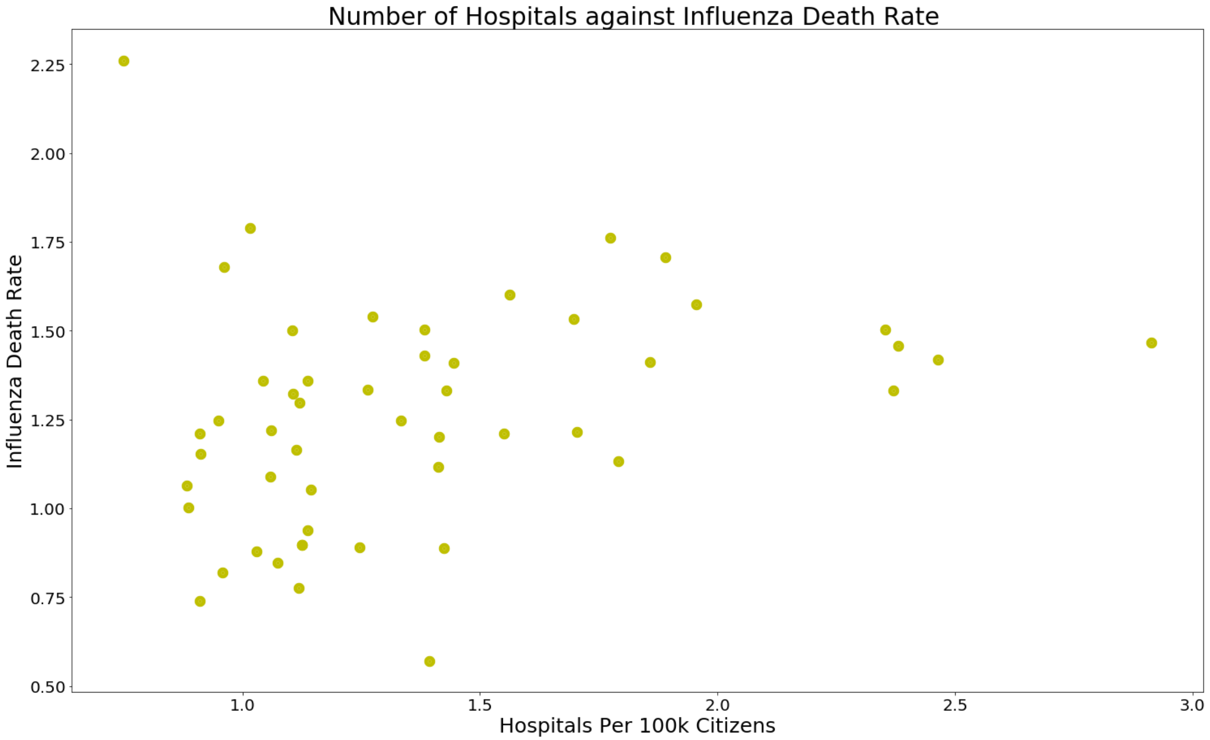
```
/opt/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:5: Set
tingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

/opt/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:8: Set
tingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

Out[43]:

	Cause Name	State	Death Rate	Age-adjusted Death Rate	Pop Density	Urgent Care Units	NumberHospitals	StaffedBeds	Tota
0	Influenza and pneumonia	Alabama	1.411794	18.8	94.4	2.02	1.857262	15,330	
1	Influenza and pneumonia	Alaska	0.571429	14.1	1.2	2.37	1.392758	1,235	
2	Influenza and pneumonia	Arizona	0.897540	10.0	56.3	2.00	1.125328	13,416	
3	Influenza and pneumonia	Arkansas	1.762379	20.7	56.0	1.19	1.774744	7,873	

4	Influenza and pneumonia	California	1.154132	14.7	239.1	1.42	0.912016	74,624

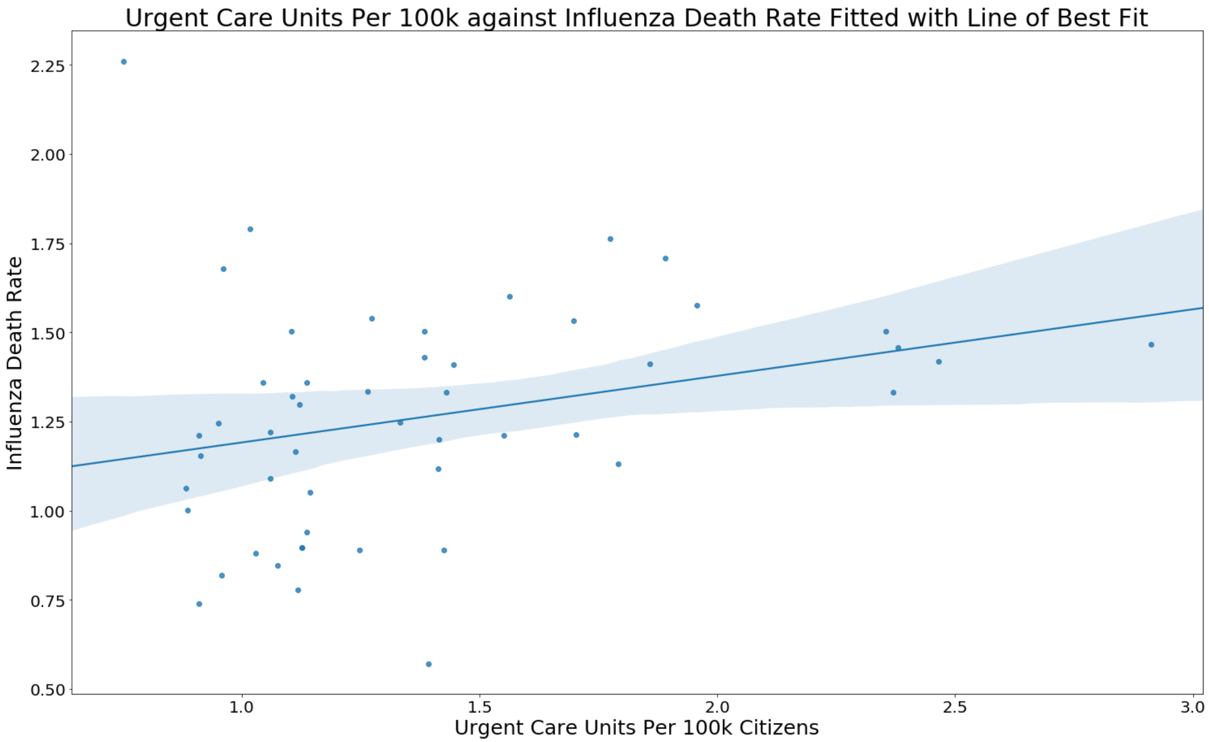
In [44]:
```
figure, ax = plt.subplots(figsize=(25,15))
main_data.plot.scatter(x="NumberHospitals", y = "Death Rate",ax=ax,c=
'y',linewidths=9)
ax.set_title("Number of Hospitals against Influenza Death Rate ",fontsi
ze=30)
ax.set_ylabel("Influenza Death Rate", size = 25)
ax.set_xlabel("Hospitals Per 100k Citizens", size = 25)
ax.tick_params(axis='y', which='major', labelsize=20)
ax.tick_params(axis='x', which='major', labelsize=20)
```



In [45]:
```
figure, ax = plt.subplots(figsize=(25,15))
#sb.set(color_codes=True)
```

```python
x = main_data["NumberHospitals"].astype(float)
y = main_data["Death Rate"].astype(float)
ax = sb.regplot(x=x, y=y, data=main_data)
ax.tick_params(axis='y', which='major', labelsize=20)
ax.tick_params(axis='x', which='major', labelsize=20)
ax.set_ylabel("Influenza Death Rate", size = 25)
ax.set_xlabel("Urgent Care Units Per 100k Citizens", size = 25)
ax.set_title("Urgent Care Units Per 100k against Influenza Death Rate F
itted with Line of Best Fit",fontsize=30)
```

Out[45]:
```
Text(0.5, 1.0, 'Urgent Care Units Per 100k against Influenza Death Rate
Fitted with Line of Best Fit')
```



Hospitals Regression

In [46]:
```python
hosp_reg = main_data.copy(deep=True)
hosp_reg.columns = hosp_reg.columns.str.strip().str.lower().str.replace
(" ", "_").str.replace("-", "_")
reg = smf.ols("death_rate ~ numberhospitals", data = hosp_reg).fit()
print(reg.summary())
```

```
                            OLS Regression Results

==============================================================================
=======
Dep. Variable:             death_rate   R-squared:
  0.078
Model:                            OLS   Adj. R-squared:
  0.059
Method:                 Least Squares   F-statistic:
  4.158
Date:                Wed, 13 May 2020   Prob (F-statistic):
0.0468
Time:                        20:04:34   Log-Likelihood:
-11.340
No. Observations:                  51   AIC:
  26.68
Df Residuals:                      49   BIC:
  30.54
Df Model:                           1

Covariance Type:            nonrobust

==============================================================================
============
                      coef    std err          t      P>|t|      [0.025
      0.975]
------------------------------------------------------------------------------
------------
Intercept           1.0046      0.133      7.532      0.000       0.737
       1.273
numberhospitals     0.1867      0.092      2.039      0.047       0.003
       0.371
==============================================================================
=======
```

```
Omnibus:                       12.283   Durbin-Watson:
  1.838
Prob(Omnibus):                  0.002   Jarque-Bera (JB):
16.300
Skew:                           0.808   Prob(JB):
0.000289
Kurtosis:                       5.250   Cond. No.
   6.47
========================================================================
=======

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

Based on the regression, there is a causal correlation between the amount of hosptials in a state, and the deaths to the flu, however not in the trend we expected. The more hospitals there are in a state, the more influenza deaths there are. On top of this, the results are not strongly explanatory, holding a R-squared value of only .078.

An explanation here could be that more hospitals means people have more access to medical care for influenza. Therefore, the greater number of hospitals could increase the number of reported incidents, meanwhile, areas with fewer hospitals could have an equal or higher rate but simply fewer reported incidents.

Combined Regression

In [47]:
```
reg = smf.ols("death_rate ~ urgent_care_units + pop_density + numberhos
pitals", data = hosp_reg).fit()
print(reg.summary())
```

```
                            OLS Regression Results

========================================================================
=======
Dep. Variable:             death_rate   R-squared:
```

```
  0.392
Model:                            OLS   Adj. R-squared:
  0.353
Method:                 Least Squares   F-statistic:
  10.09
Date:                Wed, 13 May 2020   Prob (F-statistic):
3.02e-05
Time:                        20:04:34   Log-Likelihood:                -
0.73932
No. Observations:                  51   AIC:
  9.479
Df Residuals:                      47   BIC:
  17.21
Df Model:                           3

Covariance Type:            nonrobust

========================================================================
==============
                        coef    std err          t      P>|t|      [0.0
25      0.975]
------------------------------------------------------------------------
--------------
Intercept             0.9955      0.137      7.272      0.000       0.7
20       1.271
urgent_care_units    -0.0913      0.052     -1.745      0.088      -0.1
97       0.014
pop_density        4.367e-05   9.89e-06      4.417      0.000    2.38e-
05    6.36e-05
numberhospitals       0.2875      0.079      3.643      0.001       0.1
29       0.446
========================================================================
=======
Omnibus:                        0.134   Durbin-Watson:
  2.110
Prob(Omnibus):                  0.935   Jarque-Bera (JB):
  0.064
Skew:                           0.076   Prob(JB):
  0.969
```

```
Kurtosis:                       2.915   Cond. No.
1.60e+04
=======================================================================
=======

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 1.6e+04. This might indicate that th
ere are
strong multicollinearity or other numerical problems.
```

Conclusion

We ran three regression tests. None were particiularly explanatory of influenza, however they did provide some food for thought. Between the three regressions we see that there is strong collinearity, which means is that the factors we are tested have high correlation between each other.

Given what we tested, we think it is safe to conclude that the larger prescence of influenza deaths in New York certainly is statistically significant, however the root causes of cannot be drawn from these variables. At this point, it is likely that there are other factors that influence the influenza death rate that were not accounted for. For example, New York City receives a large number of visitors each year, each of whom could be carriers of illness thus making it faster spread, especially with the prolific use of public transportation.

Looking at the combined regression, while it does hold some explanatory value, as shown by the R-squared value, p-value, and F-statistic, it fails to provide a thorough and robust explanation of the the root causes of high or low influenza rates. A worthwhile next step that we would like to further investigate is the relationship between these variables and the spread of COVID-19 in the United States. It would be interesting to see how these variables behave with a different virus, and if perhaps this tells an overall story about the state of viral infection in NYC vs the US, and if our variables behave in a similar way.

d. Relationship Between Influenza Analysis and COVID-19 Impact

source:

https://raw.githubusercontent.com/nytimes/covid-19-data/master/us-states.csv
https://projects.thecity.nyc/2020_03_covid-19-tracker nyc data

In [48]:

```
#load in data
covid = pd.read_csv("https://raw.githubusercontent.com/nytimes/covid-19-data/master/us-states.csv")
#get todays statistics
covid = covid.tail(55)

#drop nonstates
for index,row in covid.iterrows():
    if covid["state"][index] not in states:
        covid.drop(index, inplace=True)
#reset index
covid.reset_index(inplace=True,drop=True)

covid.head()
```

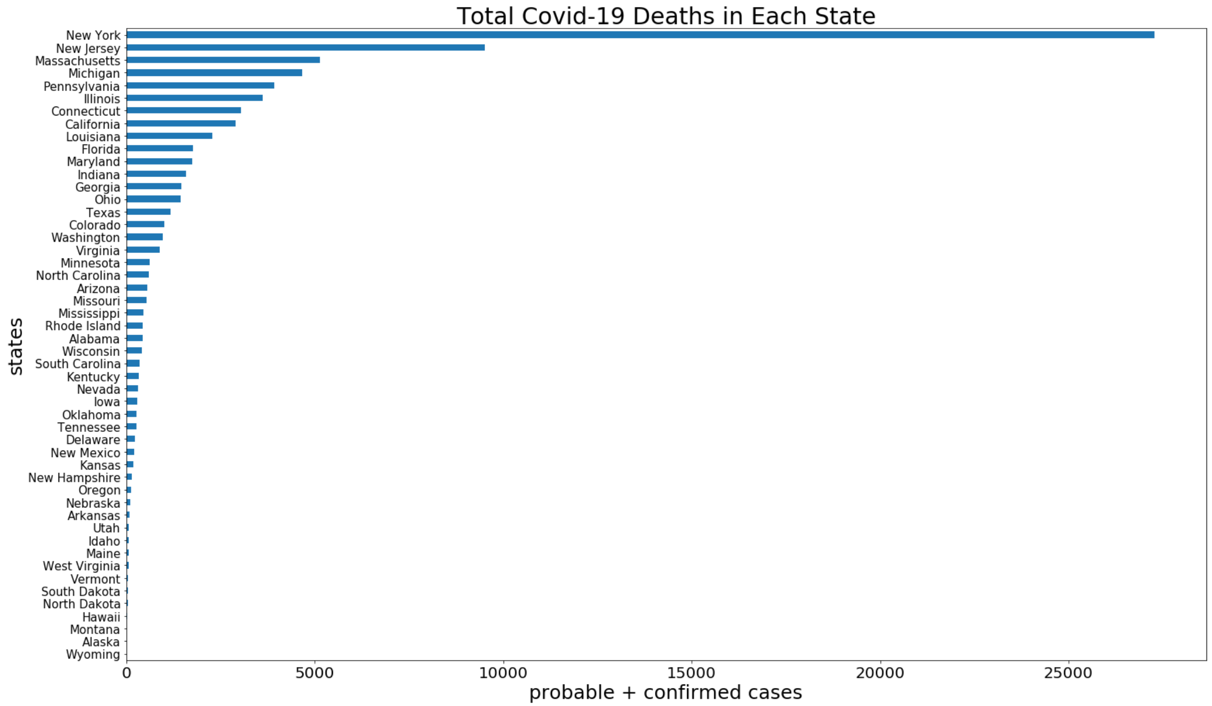
Out[48]:

	date	state	fips	cases	deaths
0	2020-05-12	Alabama	1	10464	435
1	2020-05-12	Alaska	2	383	8
2	2020-05-12	Arizona	4	11736	562
3	2020-05-12	Arkansas	5	4164	95
4	2020-05-12	California	6	71150	2902

In [49]:

```
#change the index to the state name, sort values
covid = covid.set_index("state", drop=True)
covid = covid.sort_values("deaths",ascending=True)
```

```
#plot
figure, ax = plt.subplots(figsize=(25,15))
covid["deaths"].plot.barh(ax=ax, x = "state")
ax.set_title("Total Covid-19 Deaths in Each State",fontsize=30)
ax.set_ylabel("states", size = 25)
ax.set_xlabel("probable + confirmed cases", size = 25)
ax.tick_params(axis='y', which='major', labelsize=15)
ax.tick_params(axis='x', which='major', labelsize=20)
```



In [50]:
```
#read in data
ir = pd.read_csv("agg.csv")

#drop nonstates and wrong death types
ir = ir.loc[ir["Cause Name"] == "Influenza and pneumonia"]
ir.drop(ir.loc[ir["State"]=="United States"].index,inplace=True)

#get correct years, will need for accurate test later
ir = ir.loc[ir["Year"] > 2007]
```

```
ir = ir.loc[ir["Year"] < 2015]

#turn deaths to floats
ir["Deaths"] = ir["Deaths"].str.replace(",","").astype(float)
grouped = ir.groupby(["State"],as_index=False)["Deaths"].sum()
grouped
```

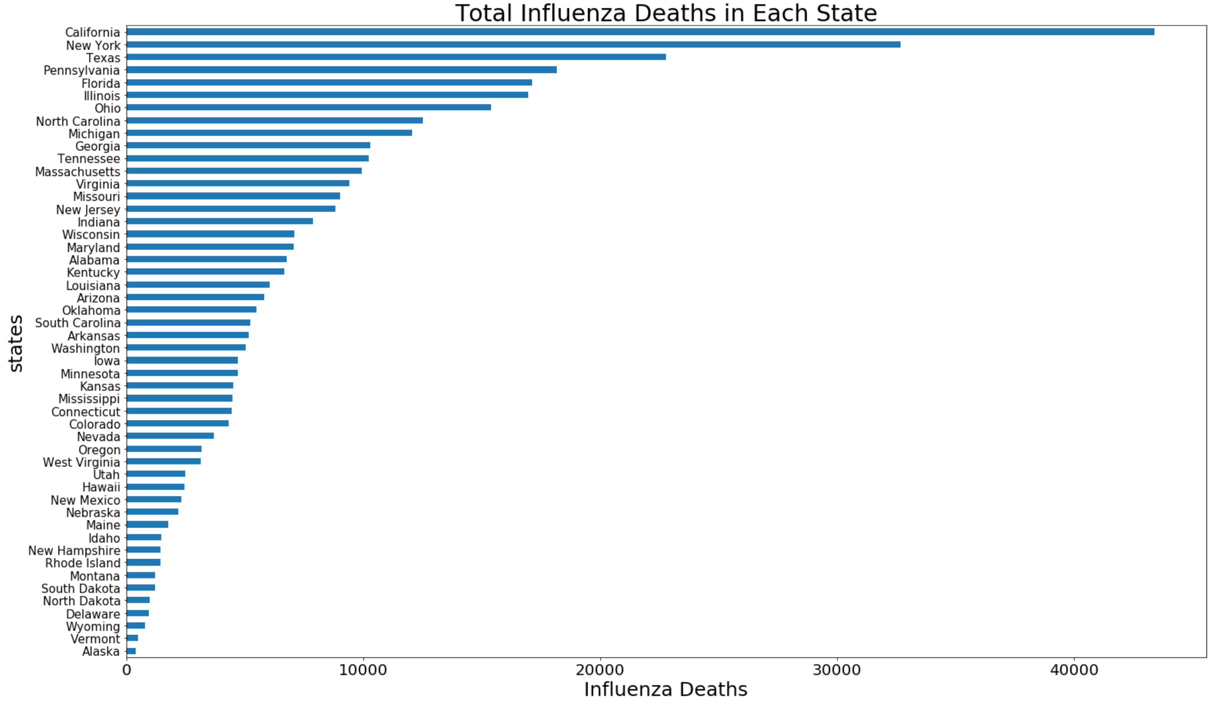
Out[50]:

	State	Deaths
0	Alabama	6765.0
1	Alaska	410.0
2	Arizona	5822.0
3	Arkansas	5163.0
4	California	43406.0
5	Colorado	4336.0
6	Connecticut	4460.0
7	Delaware	965.0
8	District of Columbia	560.0
9	Florida	17141.0
10	Georgia	10305.0
11	Hawaii	2464.0
12	Idaho	1486.0
13	Illinois	16973.0
14	Indiana	7883.0
15	Iowa	4717.0
16	Kansas	4510.0
17	Kentucky	6680.0
18	Louisiana	6068.0
19	Maine	1771.0

	State	Deaths
20	Maryland	7053.0
21	Massachusetts	9932.0
22	Michigan	12081.0
23	Minnesota	4701.0
24	Mississippi	4471.0
25	Missouri	9023.0
26	Montana	1212.0
27	Nebraska	2208.0
28	Nevada	3704.0
29	New Hampshire	1440.0
30	New Jersey	8828.0
31	New Mexico	2338.0
32	New York	32691.0
33	North Carolina	12512.0
34	North Dakota	975.0
35	Ohio	15403.0
36	Oklahoma	5513.0
37	Oregon	3170.0
38	Pennsylvania	18186.0
39	Rhode Island	1434.0
40	South Carolina	5225.0
41	South Dakota	1208.0
42	Tennessee	10247.0
43	Texas	22783.0
44	Utah	2497.0

	State	Deaths
45	Vermont	486.0
46	Virginia	9424.0
47	Washington	5036.0
48	West Virginia	3161.0
49	Wisconsin	7108.0
50	Wyoming	806.0

In [51]:
```
#change the index to the state name, sort values, drop nonstates
grouped = grouped.set_index("State", drop=True)
grouped= grouped.sort_values("Deaths",ascending=True)
grouped.drop("District of Columbia", inplace=True)
#plot
figure, ax = plt.subplots(figsize=(25,15))
grouped["Deaths"].plot.barh(ax=ax, x = "State")
ax.set_title("Total Influenza Deaths in Each State",fontsize=30)
ax.set_ylabel("states", size = 25)
ax.set_xlabel("Influenza Deaths", size = 25)
ax.tick_params(axis='y', which='major', labelsize=15)
ax.tick_params(axis='x', which='major', labelsize=20)
```



In [52]:
```
#top 10 states with most deaths to covid
covid.tail(10)
```

Out[52]:

state	date	fips	cases	deaths
Florida	2020-05-12	12	41915	1778
Louisiana	2020-05-12	22	32050	2281
California	2020-05-12	6	71150	2902
Connecticut	2020-05-12	9	34333	3041
Illinois	2020-05-12	17	83168	3617
Pennsylvania	2020-05-12	42	61407	3924
Michigan	2020-05-12	26	47946	4674

state	date	fips	cases	deaths
Massachusetts	2020-05-12	25	79332	5141
New Jersey	2020-05-12	34	140743	9508
New York	2020-05-12	36	343705	27284

In [53]:

```
#top 10 states with most deaths to flu
grouped.tail(10)
```

Out[53]:

State	Deaths
Georgia	10305.0
Michigan	12081.0
North Carolina	12512.0
Ohio	15403.0
Illinois	16973.0
Florida	17141.0
Pennsylvania	18186.0
Texas	22783.0
New York	32691.0
California	43406.0

sources:

https://worldpopulationreview.com/states/ most populous states

Looking at the two graphs visually, the trends look incredibly similar. In fact, 7 of the top states for deaths from COVID-19, are also in the top 10 for deaths from influenza between 2008-2017. This seems to imply that the areas hit hardest by COVID-19 are correlated with the same factors that lead to increased deaths from Influenza. While we have already explored several factors previously, there is a very obvious factor that we have not yet test, population. We test population density yes, but not yet population. Given these 7 shared states that were hit hardest by both COVID-19 and Influenze are all in the top 10 most populous states, this seems to be a likely causal factor.

Initially, this may seem like a trivial test, given that it should be obvious that a place with more people should have more viral cases, however, please consider two facts. The first being that our population density did not have a large amount of explanatory power, so it seems that perhaps population should also not be explanatory. The second fact being that if this were a one-to-one ratio, countries like China, India, and Indonesia would have the highest rates of COVID-19 deaths alongside the US, but they do not.

In [54]:

```
#reset the index to merge, sort alphabetically, then rest the index aga
in after sorting
covid = covid.reset_index()
covid.sort_values("state", inplace=True)
covid.reset_index(drop=True,inplace=True)
grouped = grouped.reset_index()
grouped.sort_values("State",inplace=True)
grouped.reset_index(inplace=True,drop=True)
```

regression population vs covid and influenza deaths

In [55]:

```
#merge the dataframes together
cov_inf = pd.concat([covid,grouped["Deaths"]],axis=1)
cov_inf = cov_inf.rename(columns={"cases": "Covid Cases", "deaths":"Cov
id Deaths", "Deaths":"Influenza Deaths"})
cov_inf.drop(columns= {"date", "fips"},inplace=True)
cov_inf
```

Out[55]:

	state	Covid Cases	Covid Deaths	Influenza Deaths
0	Alabama	10464	435	6765.0

	state	Covid Cases	Covid Deaths	Influenza Deaths
1	Alaska	383	8	410.0
2	Arizona	11736	562	5822.0
3	Arkansas	4164	95	5163.0
4	California	71150	2902	43406.0
5	Colorado	20103	1009	4336.0
6	Connecticut	34333	3041	4460.0
7	Delaware	6741	237	965.0
8	Florida	41915	1778	17141.0
9	Georgia	33311	1470	10305.0
10	Hawaii	624	17	2464.0
11	Idaho	2294	69	1486.0
12	Illinois	83168	3617	16973.0
13	Indiana	25676	1578	7883.0
14	Iowa	12912	289	4717.0
15	Kansas	7392	188	4510.0
16	Kentucky	7003	333	6680.0
17	Louisiana	32050	2281	6068.0
18	Maine	1477	65	1771.0
19	Maryland	34174	1756	7053.0
20	Massachusetts	79332	5141	9932.0
21	Michigan	47946	4674	12081.0
22	Minnesota	12494	614	4701.0
23	Mississippi	9908	457	4471.0
24	Missouri	10124	530	9023.0
25	Montana	461	16	1212.0

	state	Covid Cases	Covid Deaths	Influenza Deaths
26	Nebraska	8734	103	2208.0
27	Nevada	6311	321	3704.0
28	New Hampshire	3239	142	1440.0
29	New Jersey	140743	9508	8828.0
30	New Mexico	5212	219	2338.0
31	New York	343705	27284	32691.0
32	North Carolina	15402	597	12512.0
33	North Dakota	1571	38	975.0
34	Ohio	25257	1436	15403.0
35	Oklahoma	4731	278	5513.0
36	Oregon	3359	130	3170.0
37	Pennsylvania	61407	3924	18186.0
38	Rhode Island	11614	444	1434.0
39	South Carolina	7927	355	5225.0
40	South Dakota	3663	39	1208.0
41	Tennessee	15777	264	10247.0
42	Texas	42349	1169	22783.0
43	Utah	6454	73	2497.0
44	Vermont	927	54	486.0
45	Virginia	25800	891	9424.0
46	Washington	18503	972	5036.0
47	West Virginia	1378	58	3161.0
48	Wisconsin	10617	418	7108.0
49	Wyoming	675	7	806.0

In [56]:
```
population = []
for key in states_population.keys():
    population.append(states_population[key])
cov_inf["population"] = population
cov_inf
```

Out[56]:

	state	Covid Cases	Covid Deaths	Influenza Deaths	population
0	Alabama	10464	435	6765.0	4791774.0
1	Alaska	383	8	410.0	717500.0
2	Arizona	11736	562	5822.0	6486619.0
3	Arkansas	4164	95	5163.0	2929563.0
4	California	71150	2902	43406.0	37609207.0
5	Colorado	20103	1009	4336.0	5117716.0
6	Connecticut	34333	3041	4460.0	3579097.0
7	Delaware	6741	237	965.0	907452.0
8	Florida	41915	1778	17141.0	19103407.0
9	Georgia	33311	1470	10305.0	9793851.0
10	Hawaii	624	17	2464.0	1376592.0
11	Idaho	2294	69	1486.0	1582556.0
12	Illinois	83168	3617	16973.0	12843433.0
13	Indiana	25676	1578	7883.0	6512074.0
14	Iowa	12912	289	4717.0	3062976.0
15	Kansas	7392	188	4510.0	2863152.0
16	Kentucky	7003	333	6680.0	4360213.0
17	Louisiana	32050	2281	6068.0	4557963.0
18	Maine	1477	65	1771.0	1328999.0
19	Maryland	34174	1756	7053.0	5827970.0
20	Massachusetts	79332	5141	9932.0	6612387.0

	state	Covid Cases	Covid Deaths	Influenza Deaths	population
21	Michigan	47946	4674	12081.0	9907799.0
22	Minnesota	12494	614	4701.0	5345641.0
23	Mississippi	9908	457	4471.0	2973658.0
24	Missouri	10124	530	9023.0	6000784.0
25	Montana	461	16	1212.0	998050.0
26	Nebraska	8734	103	2208.0	1839140.0
27	Nevada	6311	321	3704.0	2727024.0
28	New Hampshire	3239	142	1440.0	1321839.0
29	New Jersey	140743	9508	8828.0	8807592.0
30	New Mexico	5212	219	2338.0	2065178.0
31	New York	343705	27284	32691.0	19463610.0
32	North Carolina	15402	597	12512.0	9639684.0
33	North Dakota	1571	38	975.0	691567.0
34	Ohio	25257	1436	15403.0	11550537.0
35	Oklahoma	4731	278	5513.0	3782356.0
36	Oregon	3359	130	3170.0	3866453.0
37	Pennsylvania	61407	3924	18186.0	12722725.0
38	Rhode Island	11614	444	1434.0	1054358.0
39	South Carolina	7927	355	5225.0	4674468.0
40	South Dakota	3663	39	1208.0	824137.0
41	Tennessee	15777	264	10247.0	6398327.0
42	Texas	42349	1169	22783.0	25633010.0
43	Utah	6454	73	2497.0	2807516.0
44	Vermont	927	54	486.0	625610.0
45	Virginia	25800	891	9424.0	8087159.0

	state	Covid Cases	Covid Deaths	Influenza Deaths	population
46	Washington	18503	972	5036.0	6813789.0
47	West Virginia	1378	58	3161.0	1851094.0
48	Wisconsin	10617	418	7108.0	5701539.0
49	Wyoming	675	7	806.0	568254.0

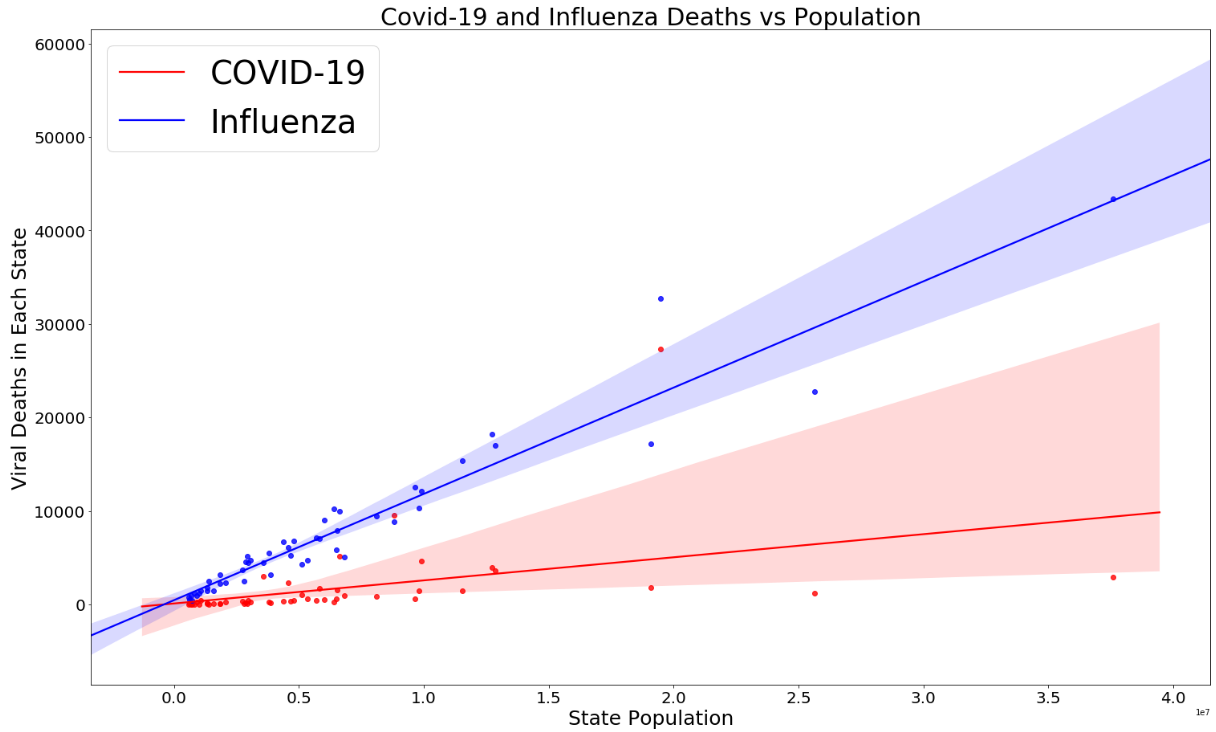
Visualization

In [57]:

```
figure, ax = plt.subplots(figsize=(25,15))

#plot
x = cov_inf["population"].astype(float)
y = cov_inf["Covid Deaths"].astype(float)
ax = sb.regplot(x=x, y=y, data=cov_inf, color="r")
ax = sb.regplot(x=x, y=cov_inf["Influenza Deaths"].astype(float), color
 = "b")
ax.set_title("Covid-19 and Influenza Deaths vs Population",fontsize=30)
ax.set_ylabel("Viral Deaths in Each State", size = 25)
ax.set_xlabel("State Population", size = 25)
ax.tick_params(axis='y', which='major', labelsize=20)
ax.tick_params(axis='x', which='major', labelsize=20)
ax.legend(["COVID-19", "Influenza"], fontsize = 40, loc="upper left")
```

Out[57]:

```
<matplotlib.legend.Legend at 0x1a21119d90>
```



PLEASE NOTE: The above graph was obtained with usage of LIVE data, what you see might be different than what we saw when we did our testing.

In [ ]:

In [58]:

```
cov_reg = cov_inf.copy(deep=True)
cov_reg.columns = cov_inf.columns.str.strip().str.lower().str.replace(" ", "_").str.replace("-", "_")
reg = smf.ols("covid_deaths ~ population", data = cov_reg).fit()
print(reg.summary())
```

```
                            OLS Regression Results
==============================================================================
```

```
=======
Dep. Variable:           covid_deaths   R-squared:
  0.175
Model:                            OLS   Adj. R-squared:
  0.158
Method:                 Least Squares   F-statistic:
  10.16
Date:                Wed, 13 May 2020   Prob (F-statistic):
0.00252
Time:                        20:04:39   Log-Likelihood:
-481.47
No. Observations:                  50   AIC:
  966.9
Df Residuals:                      48   BIC:
  970.8
Df Model:                           1

Covariance Type:            nonrobust

=======================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
-----------------------------------------------------------------------
-------
Intercept    102.6133    716.897      0.143      0.887   -1338.805    1
544.032
population     0.0002   7.75e-05      3.188      0.003    9.12e-05
  0.000
=======================================================================
=======
Omnibus:                       83.702   Durbin-Watson:
  2.060
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1
463.591
Skew:                           4.481   Prob(JB):
   0.00
Kurtosis:                      27.944   Cond. No.
1.25e+07
```

```
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.25e+07. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [59]:

```
cov_reg = cov_inf.copy(deep=True)
cov_reg.columns = cov_inf.columns.str.strip().str.lower().str.replace(" ", "_").str.replace("-", "_")
reg = smf.ols("influenza_deaths ~ population", data = cov_reg).fit()
print(reg.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:       influenza_deaths   R-squared:                       0.925
Model:                            OLS   Adj. R-squared:                  0.923
Method:                 Least Squares   F-statistic:                     590.7
Date:                Wed, 13 May 2020   Prob (F-statistic):           1.25e-28
Time:                        20:04:39   Log-Likelihood:                -456.22
No. Observations:                  50   AIC:                             916.4
Df Residuals:                      48   BIC:                             920.3
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
```

```
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------
-------
Intercept    461.2597    432.612      1.066      0.292    -408.565    1
331.085
population     0.0011   4.68e-05     24.305      0.000       0.001
  0.001
========================================================================
=======
Omnibus:                       28.376   Durbin-Watson:
  2.015
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
150.281
Skew:                           1.108   Prob(JB):
2.33e-33
Kurtosis:                      11.199   Cond. No.
1.25e+07
========================================================================
=======

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 1.25e+07. This might indicate that t
here are
strong multicollinearity or other numerical problems.
```

Looking at the graph first, it is clear that while population nearly explains all of the rise in deaths attributed to Influenza, it fails to explain the total deaths from COVID-19. One explanation could be that the Flu season occurs every year. What this means is that people do not take much precautions with it, and merely accept that it will be back every year. Given that there are minimal precautions in place, states with more population simply have more cases and more deaths. However, the circumstances with COVID-19 are very different. The deaths that can be attributed to it are not simply because of population, but rather other factors likely to do with how well a city, or state, or country has prepared for the virus. This explains why countries like India and Indonesia have relatively low COVID-19 deaths in comparison to the United States.

While these results likely bolster the claim that New York City's Influenza disparity is caused largely by the population of the city, along with the other factors we tested, they do give us a reason as to believe this is true for COVID-19, at least not completely.

In [ ]:

```

```

3. Unintentional Injuries

a. US Death Rate for Accidental Deaths

First, using the file "major_causes_rates.csv", visualize the trend for age adjusted death rates for accidental deaths in the US.
Source: https://catalog.data.gov/dataset/nchs-age-adjusted-death-rates-for-selected-major-causes-of-death

In [60]:

```
rates = pd.read_csv("major_causes_rates.csv")
rates
```

Out[60]:

	Year	Cause	Age Adjusted Death Rate
0	1900	Heart Disease	265.4
1	1901	Heart Disease	272.6
2	1902	Heart Disease	285.2
3	1903	Heart Disease	304.5
4	1904	Heart Disease	331.5
...	...	...	...
600	1900	Influenza and Pneumonia	40362.0

	Year	Cause	Age Adjusted Death Rate
601	1900	Tuberculosis	38820.0
602	1900	Diarrhea/Enteritis/Ulcerative Colitis	28491.0
603	1900	Heart Disease	27427.0
604	1900	Stroke	21353.0

605 rows × 3 columns

In [61]:
```
rates.dtypes
```

Out[61]:
```
Year                          int64
Cause                        object
Age Adjusted Death Rate     float64
dtype: object
```

In [62]:
```
rates['Cause'].unique()
```

Out[62]:
```
array(['Heart Disease', 'Cancer', 'Accidents', 'Stroke',
       'Influenza and Pneumonia', 'Chronic Respiratory Diseases',
       'Vascular Lesions', 'Certain Diseases of Infancy', 'Tuberculosi
s',
       'Diarrhea/Enteritis/Ulcerative Colitis'], dtype=object)
```

In [63]:
```
#create dataframe of only 'Accidents' rates, and eliminate outliers
acc = rates.loc[rates['Cause'] == 'Accidents']
acc = acc.loc[acc['Age Adjusted Death Rate'] <= 1000]
acc
```

Out[63]:

	Year	Cause	Age Adjusted Death Rate
236	1900	Accidents	90.3
237	1901	Accidents	109.3
238	1902	Accidents	93.6
239	1903	Accidents	106.9

	Year	Cause	Age Adjusted Death Rate
240	1904	Accidents	112.8
...	...	...	...
349	2013	Accidents	39.4
350	2014	Accidents	40.5
351	2015	Accidents	43.2
352	2016	Accidents	47.4
353	2017	Accidents	49.4

118 rows × 3 columns

In [64]:

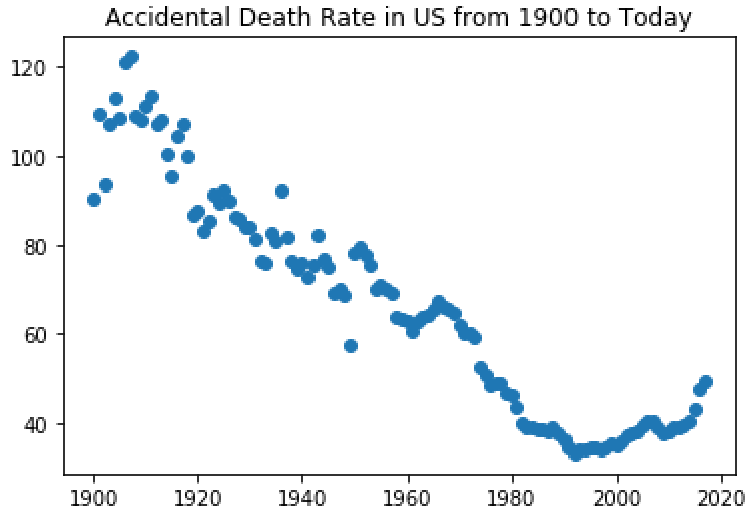
```
#sort based on the year in ascending order
acc = acc.sort_values('Year')
```

In [65]:

```
x = acc['Year']
y = acc['Age Adjusted Death Rate']
plt.scatter(x, y)
plt.title("Accidental Death Rate in US from 1900 to Today")
```

Out[65]:

```
Text(0.5, 1.0, 'Accidental Death Rate in US from 1900 to Today')
```



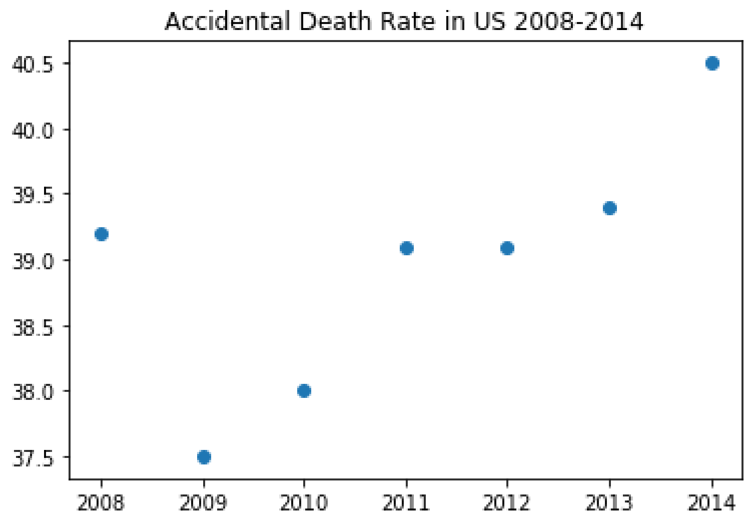
In [66]:
```
acc = acc.loc[acc['Year'] <= 2014 ]
acc = acc.loc[acc['Year'] >= 2008 ]
acc
```

Out[66]:

	Year	Cause	Age Adjusted Death Rate
344	2008	Accidents	39.2
345	2009	Accidents	37.5
346	2010	Accidents	38.0
347	2011	Accidents	39.1
348	2012	Accidents	39.1
349	2013	Accidents	39.4
350	2014	Accidents	40.5

In [67]:
```
x = acc['Year']
y = acc['Age Adjusted Death Rate']
plt.scatter(x, y)
plt.title("Accidental Death Rate in US 2008-2014")
```

Out[67]: Text(0.5, 1.0, 'Accidental Death Rate in US 2008-2014')



As we can see from the plot, the death rate for accidents has decreased significantly since the beginning of the 20th century, however, there has been a gradual increase in the recent years.

b. Breakdown of Unintentional Injury Mechanisms

Now, let us explore the various unintentional injuries leading to death in the US.
Source: https://catalog.data.gov/dataset/nchs-injury-mortality-united-states-65366

In [68]:
```
injury = pd.read_csv("injury_mortality.csv")
injury
```

Out[68]:

Year	Sex	Age Group (Years)	Race	Injury Mechanism	Injury Intent	Deaths	Population	Ag Specifi Rat

	Year	Sex	Age Group (Years)	Race	Injury Mechanism	Injury Intent	Deaths	Population	Ag Specifi Rat
0	2016	Both sexes	All Ages	All races	All Mechanisms	All Intentions	231991	323127513	71.79549
1	2015	Both sexes	All Ages	All races	All Mechanisms	All Intentions	214008	321418820	66.58228
2	2014	Both sexes	All Ages	All races	All Mechanisms	All Intentions	199752	318857056	62.64625
3	2013	Both sexes	All Ages	All races	All Mechanisms	All Intentions	192945	316128839	61.03366
4	2012	Both sexes	All Ages	All races	All Mechanisms	All Intentions	190385	313914040	60.64876
...	...	...	...	...	...	...	...	...	.
98275	2003	Female	75+	Hispanic	Unspecified	Legal intervention/war	0	488417	0.00000
98276	2002	Female	75+	Hispanic	Unspecified	Legal intervention/war	0	460962	0.00000
98277	2001	Female	75+	Hispanic	Unspecified	Legal intervention/war	0	435880	0.00000
98278	2000	Female	75+	Hispanic	Unspecified	Legal intervention/war	0	403973	0.00000
98279	1999	Female	75+	Hispanic	Unspecified	Legal intervention/war	0	384422	0.00000

98280 rows × 16 columns

In [69]:
```
injury.dtypes
```

Out[69]:
```
Year                                 int64
Sex                                 object
Age Group (Years)                   object
```

```
Race                                          object
Injury Mechanism                              object
Injury Intent                                 object
Deaths                                         int64
Population                                     int64
Age Specific Rate                            float64
Age Specific Rate Standard Error             float64
Age Specific Rate Lower Confidence Limit     float64
Age Specific Rate Upper Confidence Limit     float64
Age Adjusted Rate                             object
Age Adjusted Rate Standard Error              object
Age Adjusted Rate Lower Confidence Limit      object
Age Adjusted Rate Upper Confidence Limit      object
dtype: object
```

In [70]:
```
injury['Injury Intent'].unique()
```

Out[70]:
```
array(['All Intentions', 'Suicide', 'Unintentional', 'Undetermined',
       'Homicide', 'Legal intervention/war'], dtype=object)
```

In [71]:
```
unint = injury.loc[injury['Injury Intent'] == 'Unintentional']
unint = unint.loc[unint['Year'] <= 2014]
unint = unint.loc[unint['Year'] >= 2008]
unint = unint.sort_values('Year')
unint
```

Out[71]:

	Year	Sex	Age Group (Years)	Race	Injury Mechanism	Injury Intent	Deaths	Population	Age Specific Rate
92249	2008	Female	75+	Hispanic	Unspecified	Unintentional	65	631049	10.300309
65146	2008	Both sexes	65–74	All races	Poisoning	Unintentional	725	20505679	3.535606
65164	2008	Both sexes	75+	All races	Poisoning	Unintentional	571	18271942	3.125010

	Year	Sex	Age Group (Years)	Race	Injury Mechanism	Injury Intent	Deaths	Population	Age Specific Rate
20195	2008	Male	All Ages	All races	Drowning	Unintentional	2726	149489951	1.823534
65183	2008	Both sexes	All Ages	Non-Hispanic white	Poisoning	Unintentional	24855	199783797	12.440949
...	...	...	...	...	...	...	...	...	...
28415	2014	Female	25–44	Non-Hispanic white	Fall	Unintentional	119	24387162	0.487962
2879	2014	Female	65–74	Non-Hispanic black	All Mechanisms	Unintentional	390	1409606	27.667306
44902	2014	Female	All Ages	All races	Firearm	Unintentional	64	161920569	0.039526
66352	2014	Female	15–24	Non-Hispanic black	Poisoning	Unintentional	64	3367586	1.900471
2627	2014	Female	65–74	All races	All Mechanisms	Unintentional	4386	14049245	31.218759

7056 rows × 16 columns

In [72]:
```
unint['Injury Mechanism'].unique()
```

Out[72]:
```
array(['Unspecified', 'Poisoning', 'Drowning', 'All Other Transport',
       'Fire/hot object or substance', 'Suffocation', 'Cut/pierce',
       'Firearm', 'Fall', 'Motor vehicle traffic', 'All Mechanisms',
       'All Other Specified'], dtype=object)
```

In [73]:
```
unint['Race'].unique()
```

Out[73]:
```
array(['Hispanic', 'All races', 'Non-Hispanic white',
       'Non-Hispanic black'], dtype=object)
```

In [74]:
```
unint['Age Group (Years)'].unique()
```

Out[74]:
```
array(['75+', '65–74', 'All Ages', '< 15', '15–24', '25–44', '45–64'],
      dtype=object)
```

In [75]:
```
all_age = unint.loc[unint['Age Group (Years)'] == 'All Ages']
all_age_race = all_age.loc[all_age['Race']=='All races']
all_age_race_sex = all_age_race.loc[all_age_race['Sex'] == 'Both sexes'
]
all_age_race_sex_mech = all_age_race_sex.loc[all_age_race_sex['Injury M
echanism'] == 'All Mechanisms']
all_age_race_sex_mech = all_age_race_sex_mech.sort_values('Year')
all_age_race_sex_mech
```

Out[75]:

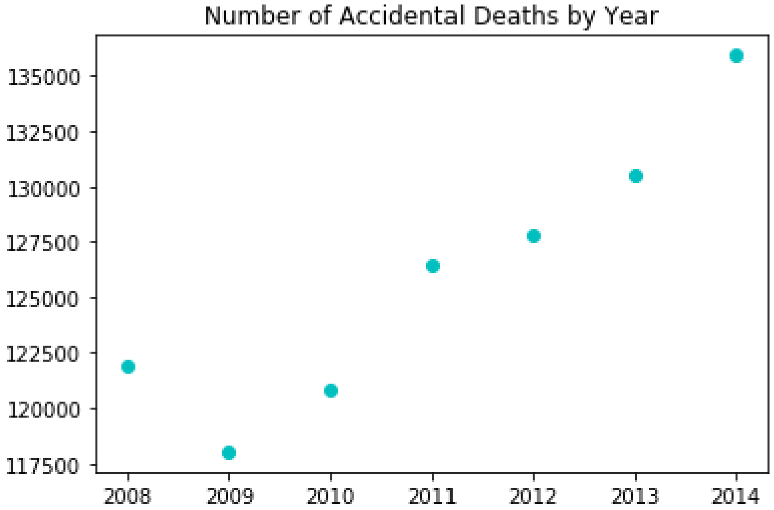
	Year	Sex	Age Group (Years)	Race	Injury Mechanism	Injury Intent	Deaths	Population	Age Specific Rate	Spe Stan E
1528	2008	Both sexes	All Ages	All races	All Mechanisms	Unintentional	121902	304093966	40.086951	0.11
1527	2009	Both sexes	All Ages	All races	All Mechanisms	Unintentional	118021	306771529	38.471954	0.11
1526	2010	Both sexes	All Ages	All races	All Mechanisms	Unintentional	120859	308745538	39.145181	0.11
1525	2011	Both sexes	All Ages	All races	All Mechanisms	Unintentional	126438	311591917	40.578074	0.11
1524	2012	Both sexes	All Ages	All races	All Mechanisms	Unintentional	127792	313914040	40.709234	0.11
1523	2013	Both sexes	All Ages	All races	All Mechanisms	Unintentional	130557	316128839	41.298668	0.11
1522	2014	Both sexes	All Ages	All races	All Mechanisms	Unintentional	135928	318857056	42.629761	0.11

All Mechanisms

Below is a graph displaying the total accidental deaths each year for both sexes, all ages, all races, and for all injury mechanisms.

In [76]:
```
x = all_age_race_sex_mech['Year']
y1 = all_age_race_sex_mech['Deaths']
plt.scatter(x, y1, color = 'c')
plt.title("Number of Accidental Deaths by Year")
```

Out[76]:
```
Text(0.5, 1.0, 'Number of Accidental Deaths by Year')
```



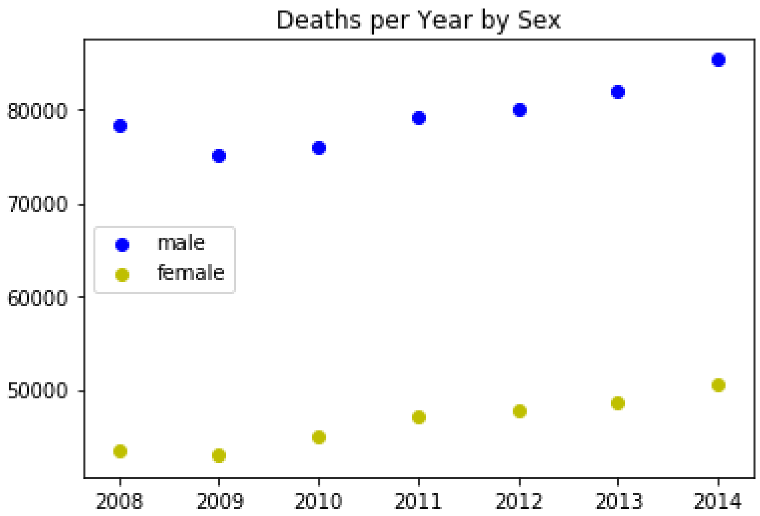
In [77]:
```
all_age_race_male = all_age_race.loc[all_age_race['Sex'] == 'Male']
all_age_race_male_mech = all_age_race_male.loc[all_age_race_male['Injur
y Mechanism'] == 'All Mechanisms']
all_age_race_male_mech = all_age_race_male_mech.sort_values('Year')

all_age_race_female = all_age_race.loc[all_age_race['Sex'] == 'Female']
all_age_race_female_mech = all_age_race_female.loc[all_age_race_female[
```

```
'Injury Mechanism'] == 'All Mechanisms']
all_age_race_female_mech = all_age_race_female_mech.sort_values('Year')
```

The below graph is the same as the one above, but broken down by sex, the blue markers are for males, while the yellow color is for females.

In [78]:
```
x = all_age_race_sex_mech['Year']
y_male = all_age_race_male_mech['Deaths']
y_female = all_age_race_female_mech['Deaths']
plt.scatter(x, y_male, color = 'b', label='male')
plt.scatter(x, y_female, color = 'y', label='female')
plt.legend(loc = "center left")
plt.title("Deaths per Year by Sex")
```

Out[78]:
```
Text(0.5, 1.0, 'Deaths per Year by Sex')
```



As we can see, regardless of the year, males have a significantly higher chance of dying as a result of unintentional injuries compared to those of females.

By Age Group

Now, lets break this down by age groups, while keeping both sexes, all races, all mechanisms constant.

In [79]:
```
#compare based off of age group, keep all races, both sexes, all mechan
isms
race = unint.loc[unint['Race']=='All races']
mech = unint.loc[unint['Injury Mechanism'] == 'All Mechanisms']
race_mech = race.loc[race['Injury Mechanism'] == 'All Mechanisms']
race_sex = race.loc[race['Sex'] == 'Both sexes']
race_sex_mech = race_sex.loc[race_sex['Injury Mechanism'] == 'All Mecha
nisms']
```

In [80]:
```
# age = < 15
child_race_sex_mech = race_sex_mech.loc[race_sex_mech['Age Group (Year
s)'] == '< 15']
child_race_sex_mech = child_race_sex_mech.sort_values('Year')
child_race_sex_mech
```

Out[80]:

	Year	Sex	Age Group (Years)	Race	Injury Mechanism	Injury Intent	Deaths	Population	Age Specific Rate	A Spec R Stand Er
1546	2008	Both sexes	< 15	All races	All Mechanisms	Unintentional	4643	60907384	7.623049	0.111
1545	2009	Both sexes	< 15	All races	All Mechanisms	Unintentional	4336	61087581	7.098006	0.107
1544	2010	Both sexes	< 15	All races	All Mechanisms	Unintentional	4147	61227213	6.773132	0.105
1543	2011	Both sexes	< 15	All races	All Mechanisms	Unintentional	4175	61201106	6.821772	0.105
1542	2012	Both sexes	< 15	All races	All Mechanisms	Unintentional	4072	61144098	6.659678	0.104
1541	2013	Both sexes	< 15	All races	All Mechanisms	Unintentional	3993	61089123	6.536352	0.103

	Year	Sex	Age Group (Years)	Race	Injury Mechanism	Injury Intent	Deaths	Population	Age Specific Rate	A Spec R Stand E
1540	2014	Both sexes	< 15	All races	All Mechanisms	Unintentional	3856	61067955	6.314277	0.101

In [81]:

```
#age =  15-24
teen_race_sex_mech = race_sex_mech.loc[race_sex_mech['Age Group (Year
s)'] == '15–24']
teen_race_sex_mech = teen_race_sex_mech.sort_values('Year')
teen_race_sex_mech
```

Out[81]:

	Year	Sex	Age Group (Years)	Race	Injury Mechanism	Injury Intent	Deaths	Population	Age Specific Rate	Spe Stan E
1564	2008	Both sexes	15–24	All races	All Mechanisms	Unintentional	14089	43391492	32.469499	0.27
1563	2009	Both sexes	15–24	All races	All Mechanisms	Unintentional	12458	43576932	28.588520	0.25
1562	2010	Both sexes	15–24	All races	All Mechanisms	Unintentional	12341	43626342	28.287955	0.25
1561	2011	Both sexes	15–24	All races	All Mechanisms	Unintentional	12330	43797875	28.152051	0.25
1560	2012	Both sexes	15–24	All races	All Mechanisms	Unintentional	11908	43943905	27.098183	0.24
1559	2013	Both sexes	15–24	All races	All Mechanisms	Unintentional	11619	43954402	26.434212	0.24
1558	2014	Both sexes	15–24	All races	All Mechanisms	Unintentional	11797	43979821	26.823665	0.24

In [82]:
```
#age = 25–44
ya_race_sex_mech = race_sex_mech.loc[race_sex_mech['Age Group (Years)']
 == '25-44']
ya_race_sex_mech = ya_race_sex_mech.sort_values('Year')
ya_race_sex_mech
```

Out[82]:

Year	Sex	Age Group (Years)	Race	Injury Mechanism	Injury Intent	Deaths	Population	Age Specific Rate	Age Specific Rate Standard Error	A Speci Rate Low Confiden Lir

In [83]:
```
# age = 45–64
a_race_sex_mech = race_sex_mech.loc[race_sex_mech['Age Group (Years)']
== '45-64']
a_race_sex_mech = a_race_sex_mech.sort_values('Year')
a_race_sex_mech
```

Out[83]:

Year	Sex	Age Group (Years)	Race	Injury Mechanism	Injury Intent	Deaths	Population	Age Specific Rate	Age Specific Rate Standard Error	A Speci Rate Low Confiden Lir

In [84]:
```
# age = 65–74
ret_race_sex_mech = race_sex_mech.loc[race_sex_mech['Age Group (Years)'
] == '65-74']
ret_race_sex_mech = ret_race_sex_mech.sort_values('Year')
ret_race_sex_mech
```

Out[84]:

Year	Sex	Age Group (Years)	Race	Injury Mechanism	Injury Intent	Deaths	Population	Age Specific Rate	Age Specific Rate Standard Error	A Speci Rate Low Confiden Lir

In [85]:
```python
# age = 75+
eld_race_sex_mech = race_sex_mech.loc[race_sex_mech['Age Group (Years)'
] == '75+']
eld_race_sex_mech = eld_race_sex_mech.sort_values('Year')
eld_race_sex_mech
```

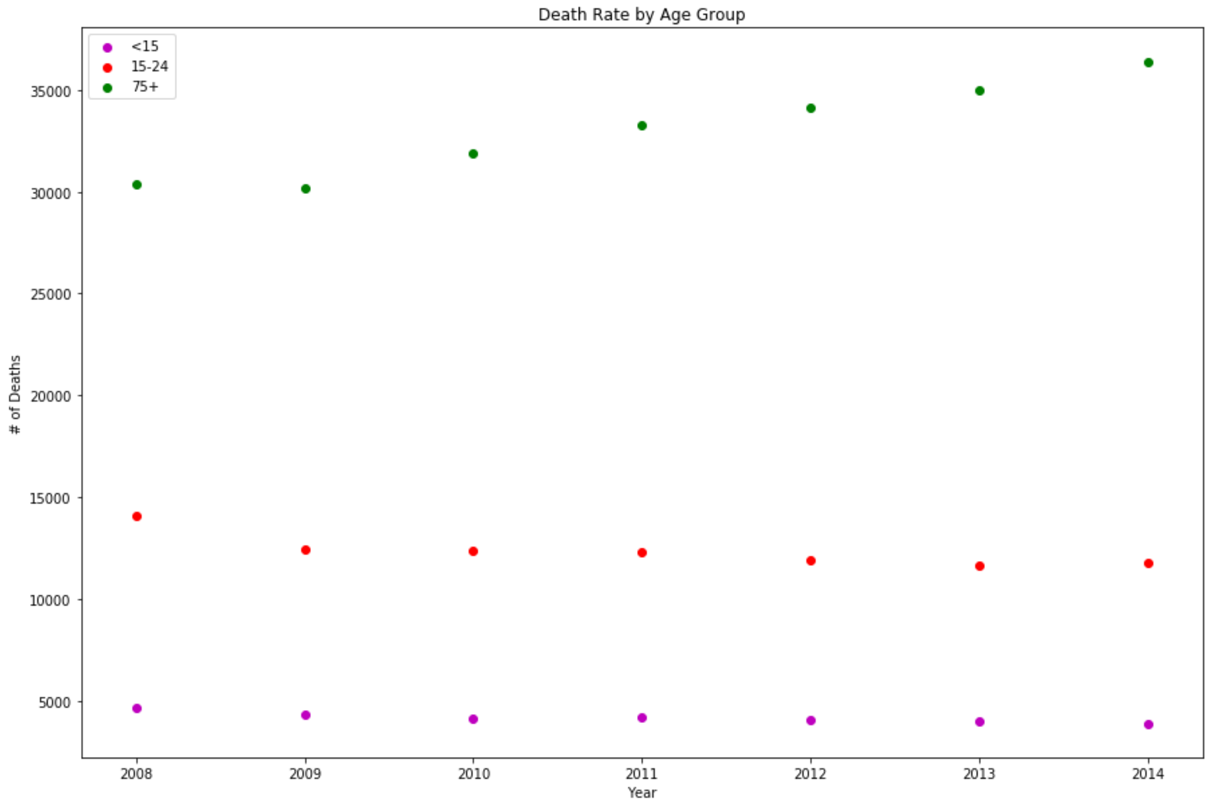
Out[85]:

	Year	Sex	Age Group (Years)	Race	Injury Mechanism	Injury Intent	Deaths	Population	Age Specific Rate	Spe Stan E
1636	2008	Both sexes	75+	All races	All Mechanisms	Unintentional	30365	18271942	166.18376	0.95
1635	2009	Both sexes	75+	All races	All Mechanisms	Unintentional	30171	18390076	164.06131	0.94
1634	2010	Both sexes	75+	All races	All Mechanisms	Unintentional	31893	18554555	171.88771	0.96
1633	2011	Both sexes	75+	All races	All Mechanisms	Unintentional	33244	18912403	175.77883	0.96
1632	2012	Both sexes	75+	All races	All Mechanisms	Unintentional	34140	19159964	178.18405	0.96
1631	2013	Both sexes	75+	All races	All Mechanisms	Unintentional	34975	19487308	179.47579	0.95
1630	2014	Both sexes	75+	All races	All Mechanisms	Unintentional	36381	19844921	183.32650	0.96

In [86]:
```python
#graph with number of deaths as y-var
x = all_age_race_sex_mech['Year']

y_child = child_race_sex_mech['Deaths']
y_teen = teen_race_sex_mech['Deaths']
y_eld = eld_race_sex_mech['Deaths']

plt.figure(figsize=(15,10))
```

```
plt.ylabel('# of Deaths')
plt.xlabel('Year')

plt.scatter(x, y_child, color = 'm', label="<15")
plt.title("Death Rate by Age Group")
plt.scatter(x, y_teen, color = 'r', label="15-24")
plt.scatter(x, y_eld, color = 'g', label='75+')
plt.legend()
```

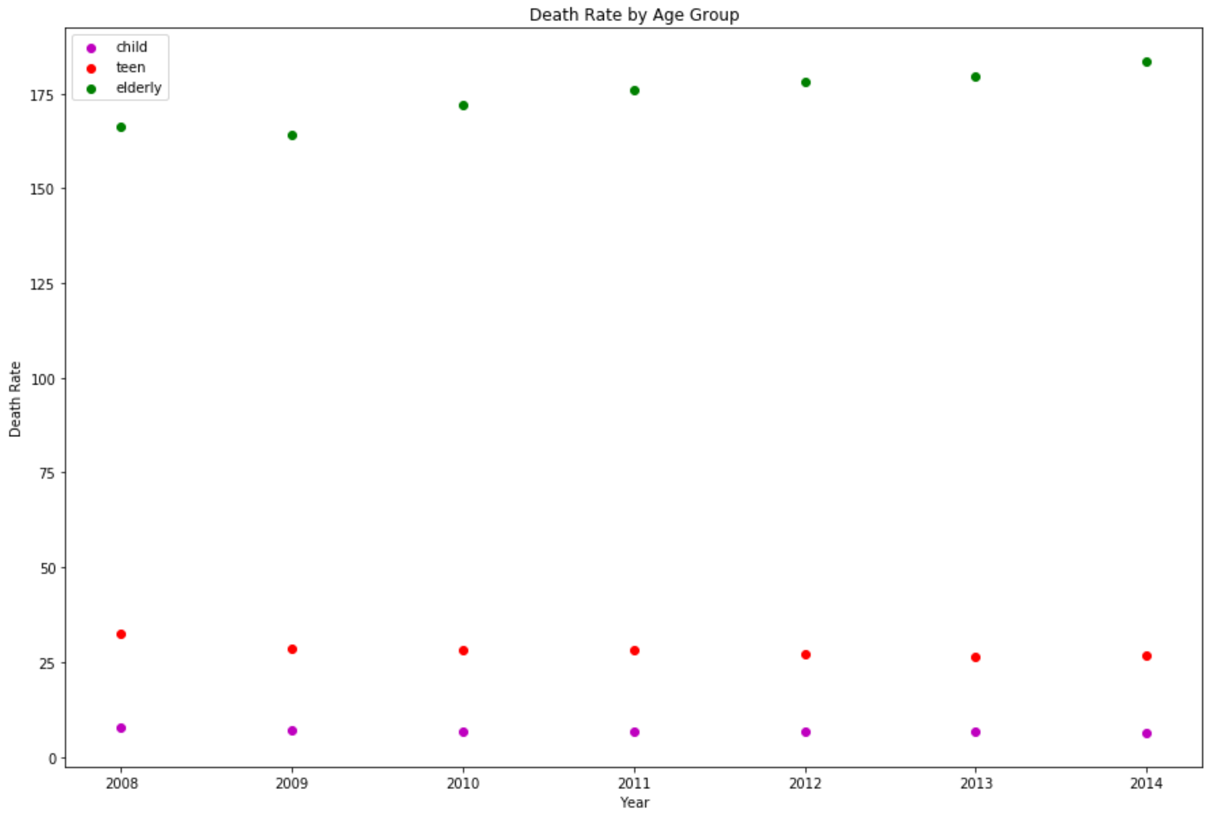
Out[86]: <matplotlib.legend.Legend at 0x1a20120dd0>



In [87]:
```
#graph with death rate as y-var
x = all_age_race_sex_mech['Year']

y_child = child_race_sex_mech['Age Specific Rate']
```

```
y_teen = teen_race_sex_mech['Age Specific Rate']
y_eld = eld_race_sex_mech['Age Specific Rate']

plt.figure(figsize=(15,10))
plt.ylabel('Death Rate')
plt.xlabel('Year')

plt.scatter(x, y_child, color = 'm',label="child")
plt.scatter(x, y_teen, color = 'r',label="teen")
plt.scatter(x, y_eld, color = 'g',label="elderly")
plt.title("Death Rate by Age Group")
plt.legend()
```

Out[87]: <matplotlib.legend.Legend at 0x1a202ce2d0>



Based off of the previous analysis, it is evident that as the population becomes older, they are more likely to die as a result of an unintentional injury. This is based off of both the number of deaths annually along with the adjusted age specific rate for each age group. While there is data missing for both sexes of all races in the ages 25-74, it is still clear that th elderly population is more suseptible to accidental deaths.

In [ ]:

```

```

Now, let's break down each injury mechanism while we hold all ages and races constant. We will compare the death rates of each mechanism amongst females and males.

Drowning

In [88]:

```
drown = all_age_race.loc[all_age_race['Injury Mechanism'] == 'Drowning'
]
drown = drown.sort_values('Year')
drown_both = drown.loc[drown['Sex'] == 'Both sexes']
drown_f = drown.loc[drown['Sex'] == 'Female']
drown_m = drown.loc[drown['Sex'] == 'Male']
```

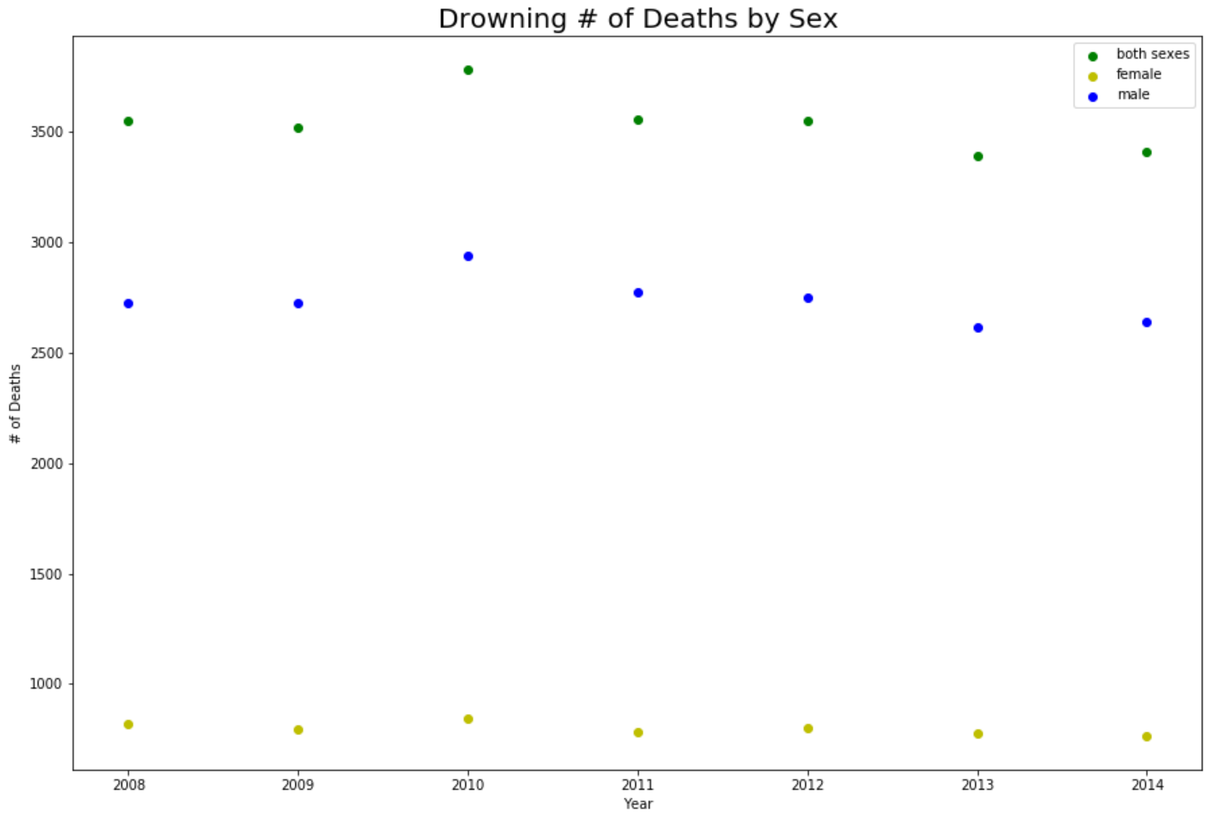
Graph with number of deaths annually

In [89]:

```
x = drown_both['Year']

y_both = drown_both['Deaths']
y_f = drown_f['Deaths']
y_m = drown_m['Deaths']

plt.figure(figsize=(15,10))
plt.ylabel('# of Deaths')
plt.xlabel('Year')

plt.scatter(x, y_both, color = 'g', label = "both sexes")
plt.scatter(x, y_f, color = 'y', label = 'female')
```

```
plt.scatter(x, y_m, color = 'b', label = 'male')
plt.title("Drowning # of Deaths by Sex", fontsize = 20)
plt.legend()
```

Out[89]: <matplotlib.legend.Legend at 0x1a21658450>

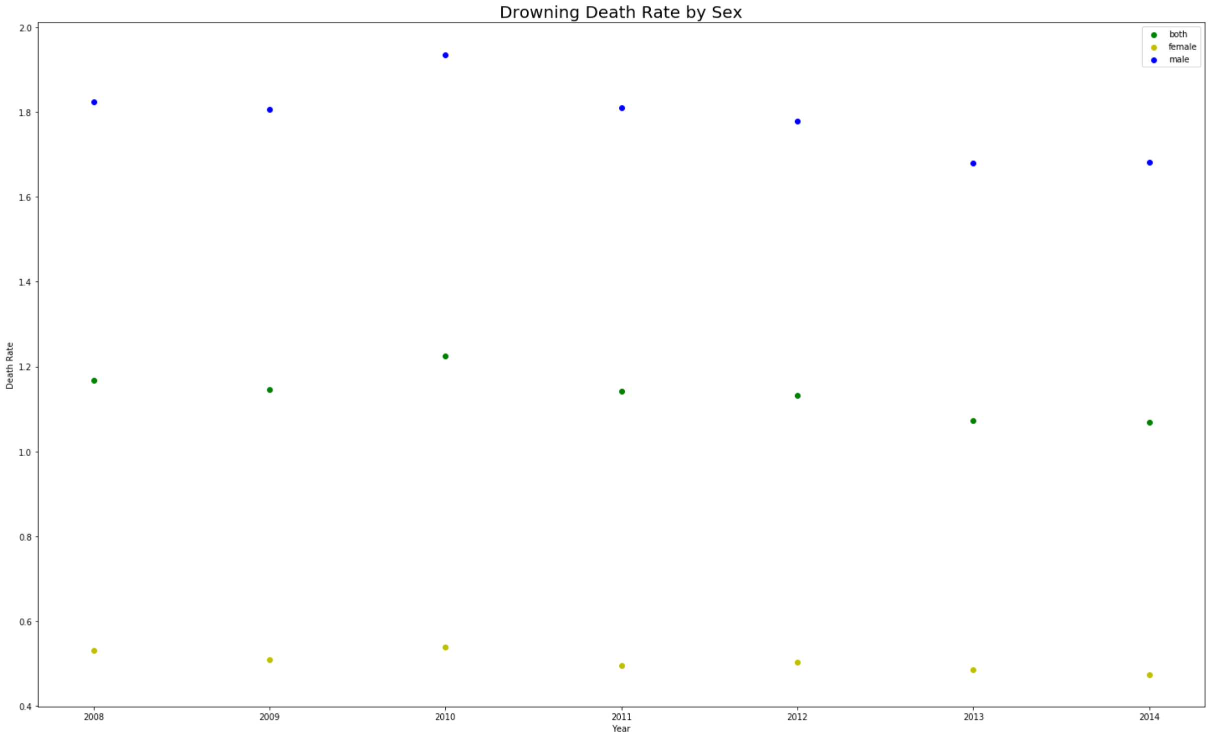


Graph with annual death rate

In [90]:
```
x = drown_both['Year']

y_both = drown_both['Age Specific Rate']
y_f = drown_f['Age Specific Rate']
y_m = drown_m['Age Specific Rate']
```

```
plt.figure(figsize=(25,15))
plt.ylabel('Death Rate')
plt.xlabel('Year')

plt.scatter(x, y_both, color = 'g', label = 'both')
plt.scatter(x, y_f, color = 'y', label = 'female')
plt.scatter(x, y_m, color = 'b', label = 'male')
plt.title("Drowning Death Rate by Sex", fontsize = 20)
plt.legend()
```

Out[90]: <matplotlib.legend.Legend at 0x1a216d65d0>



Fall

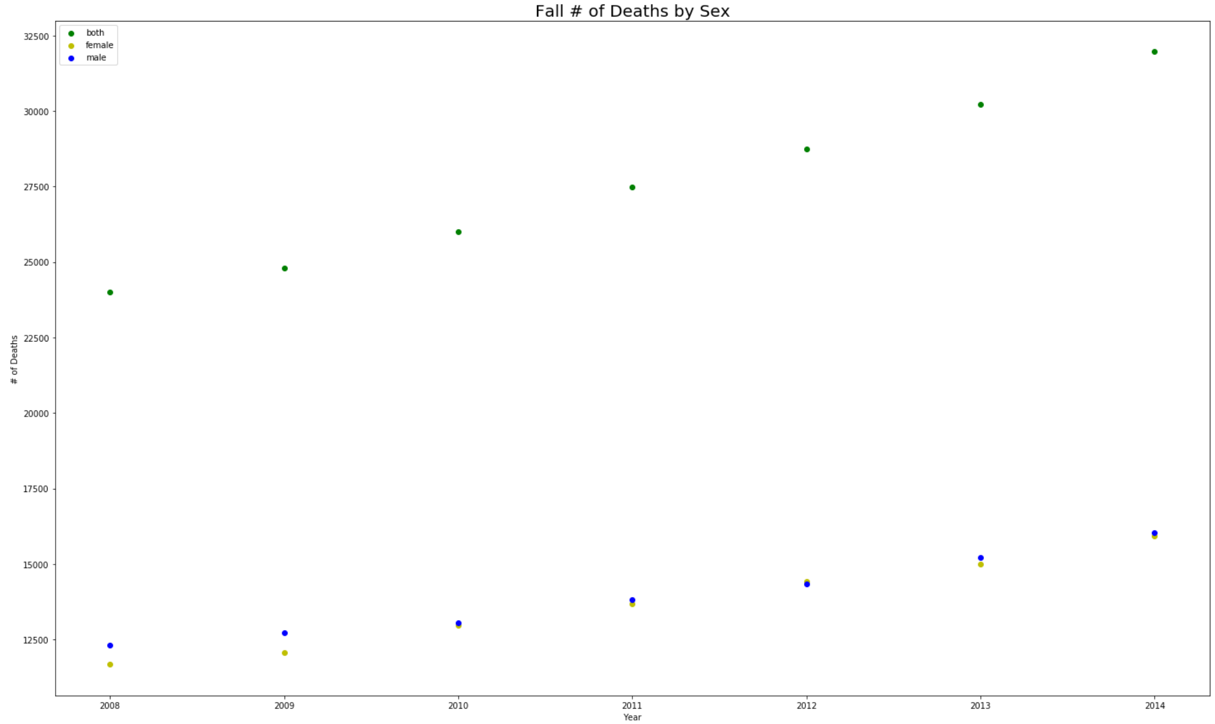
In [91]:
```
fall = all_age_race.loc[all_age_race['Injury Mechanism'] == 'Fall']
fall = fall.sort_values('Year')
```

```
fall_both = fall.loc[fall['Sex'] == 'Both sexes']
fall_f = fall.loc[fall['Sex'] == 'Female']
fall_m = fall.loc[fall['Sex'] == 'Male']
```

Graph with number of deaths annually

In [92]:
```
x = fall_both['Year']

y_both = fall_both['Deaths']
y_f = fall_f['Deaths']
y_m = fall_m['Deaths']

plt.figure(figsize=(25,15))
plt.ylabel('# of Deaths')
plt.xlabel('Year')

plt.scatter(x, y_both, color = 'g', label = 'both')
plt.scatter(x, y_f, color = 'y', label = 'female')
plt.scatter(x, y_m, color = 'b', label = 'male')
plt.title("Fall # of Deaths by Sex", fontsize = 20)
plt.legend()
```

Out[92]:
```
<matplotlib.legend.Legend at 0x1a21708f90>
```

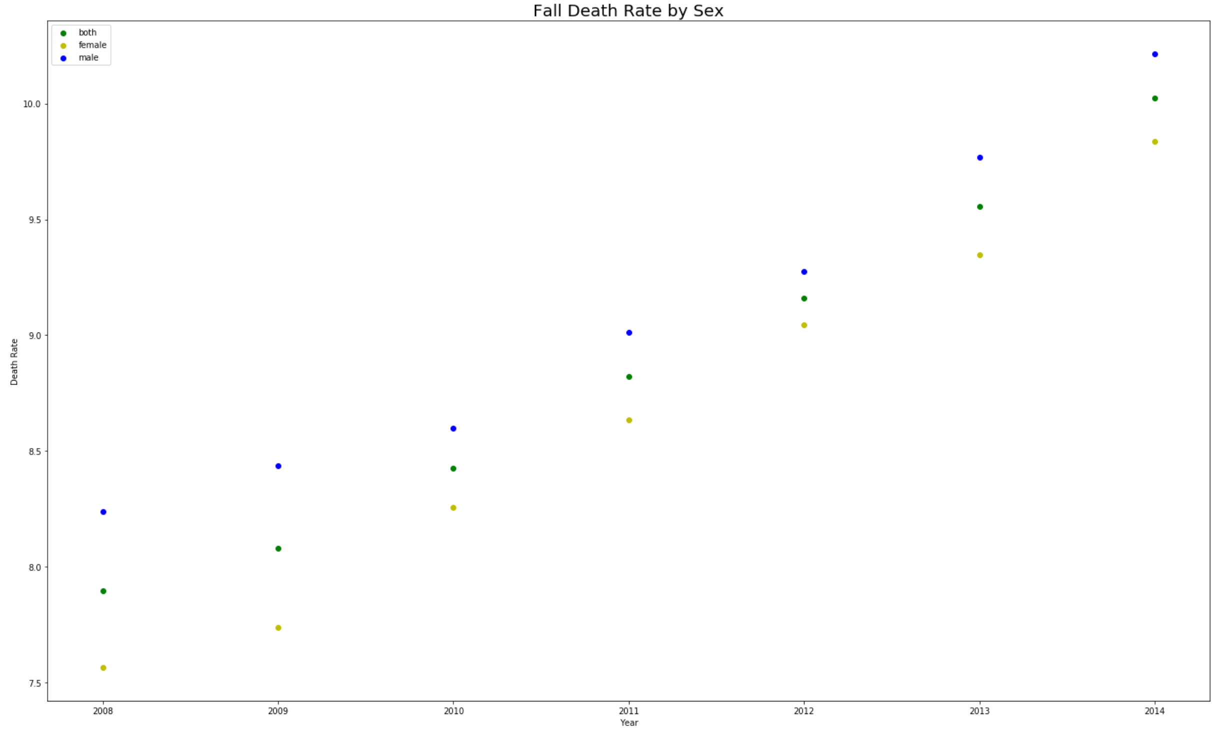


Graph with annual death rate

In [93]:
```
x = fall_both['Year']

y_both = fall_both['Age Specific Rate']
y_f = fall_f['Age Specific Rate']
y_m = fall_m['Age Specific Rate']

plt.figure(figsize=(25,15))
plt.ylabel('Death Rate')
plt.xlabel('Year')

plt.scatter(x, y_both, color = 'g', label = 'both')
plt.scatter(x, y_f, color = 'y', label = 'female')
plt.scatter(x, y_m, color = 'b', label = 'male')
```

```
plt.title("Fall Death Rate by Sex", fontsize=20)
plt.legend()
```

Out[93]: <matplotlib.legend.Legend at 0x1a21bc96d0>



There is not a large difference in death due to falls in terms of gender, they are actually almost equal. This is different from previous analyses.

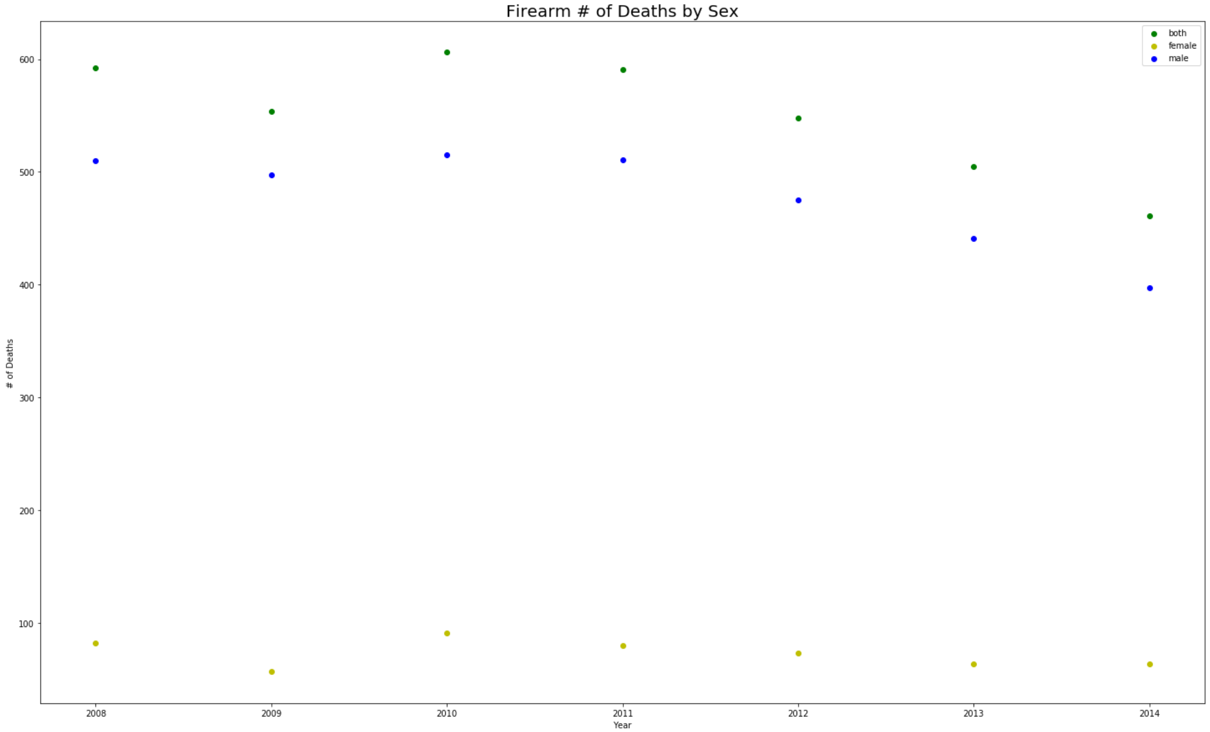
Firearms

In [94]:
```
fa = all_age_race.loc[all_age_race['Injury Mechanism'] == 'Firearm']
fa = fa.sort_values('Year')
fa_both = fa.loc[fa['Sex'] == 'Both sexes']
fa_f = fa.loc[fa['Sex'] == 'Female']
fa_m = fa.loc[fa['Sex'] == 'Male']
```

Graph with number of deaths annually

In [95]:
```
x = fa_both['Year']

y_both = fa_both['Deaths']
y_f = fa_f['Deaths']
y_m = fa_m['Deaths']

plt.figure(figsize=(25,15))
plt.ylabel('# of Deaths')
plt.xlabel('Year')

plt.scatter(x, y_both, color = 'g', label = 'both')
plt.scatter(x, y_f, color = 'y', label = 'female')
plt.scatter(x, y_m, color = 'b', label = 'male')
plt.title("Firearm # of Deaths by Sex", fontsize = 20)
plt.legend()
```

Out[95]:
```
<matplotlib.legend.Legend at 0x1a2261a290>
```

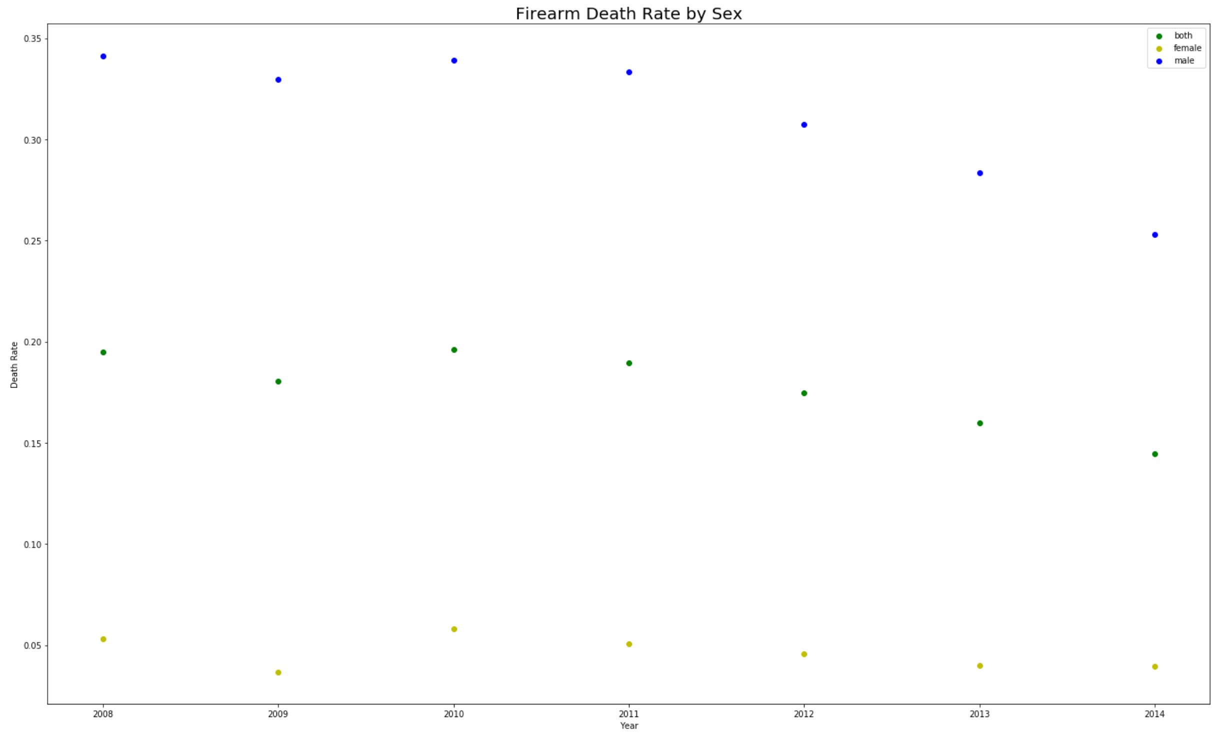


Graph with annual death rate

In [96]:
```
x = fa_both['Year']

y_both = fa_both['Age Specific Rate']
y_f = fa_f['Age Specific Rate']
y_m = fa_m['Age Specific Rate']

plt.figure(figsize=(25,15))
plt.ylabel('Death Rate')
plt.xlabel('Year')

plt.scatter(x, y_both, color = 'g', label = 'both')
plt.scatter(x, y_f, color = 'y', label = 'female')
plt.scatter(x, y_m, color = 'b', label = 'male')
```

```
plt.title("Firearm Death Rate by Sex", fontsize = 20)
plt.legend()
```

Out[96]: <matplotlib.legend.Legend at 0x1a226c9350>



In [ ]:

Cut/pierce

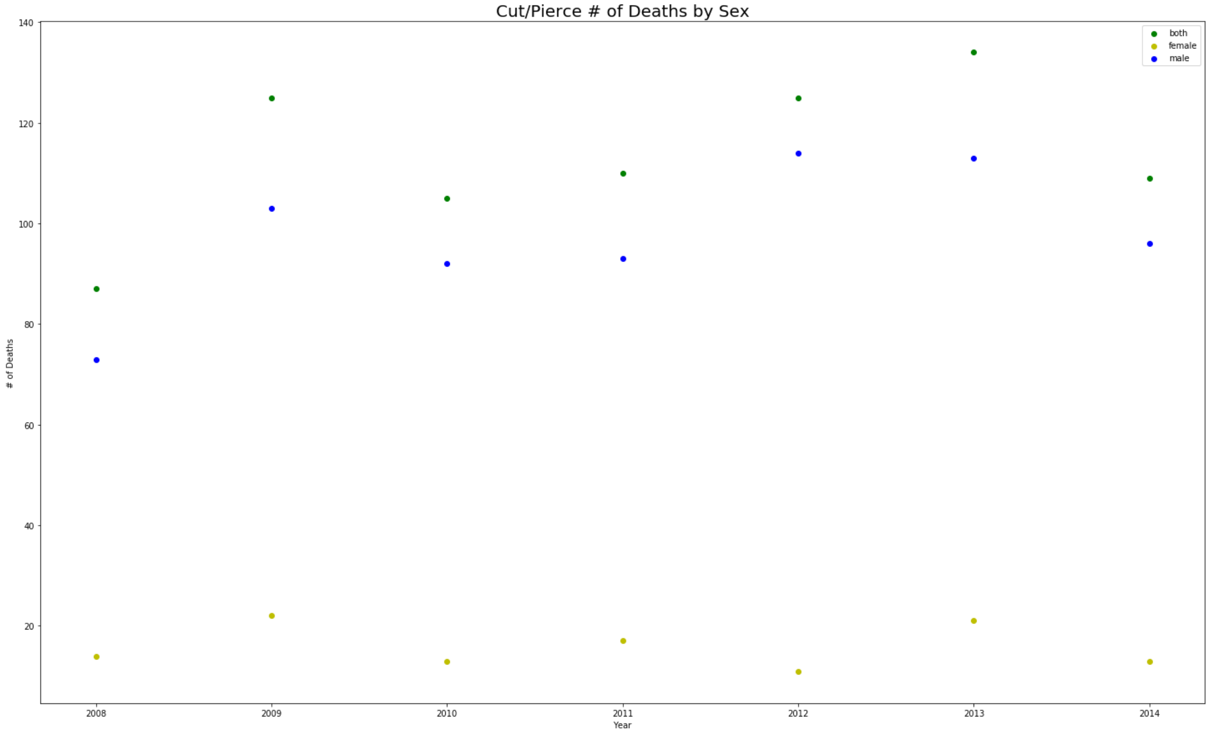
In [97]:

```
cp = all_age_race.loc[all_age_race['Injury Mechanism'] == 'Cut/pierce']
cp = cp.sort_values('Year')
cp_both = cp.loc[cp['Sex'] == 'Both sexes']
cp_f = cp.loc[cp['Sex'] == 'Female']
cp_m = cp.loc[cp['Sex'] == 'Male']
```

Graph with number of deaths annually

In [98]:
```
x = cp_both['Year']

y_both = cp_both['Deaths']
y_f = cp_f['Deaths']
y_m = cp_m['Deaths']

plt.figure(figsize=(25,15))
plt.ylabel('# of Deaths')
plt.xlabel('Year')

plt.scatter(x, y_both, color = 'g', label = 'both')
plt.scatter(x, y_f, color = 'y', label = 'female')
plt.scatter(x, y_m, color = 'b', label = 'male')
plt.title("Cut/Pierce # of Deaths by Sex", fontsize = 20)
plt.legend()
```

Out[98]:
```
<matplotlib.legend.Legend at 0x1a2286b3d0>
```

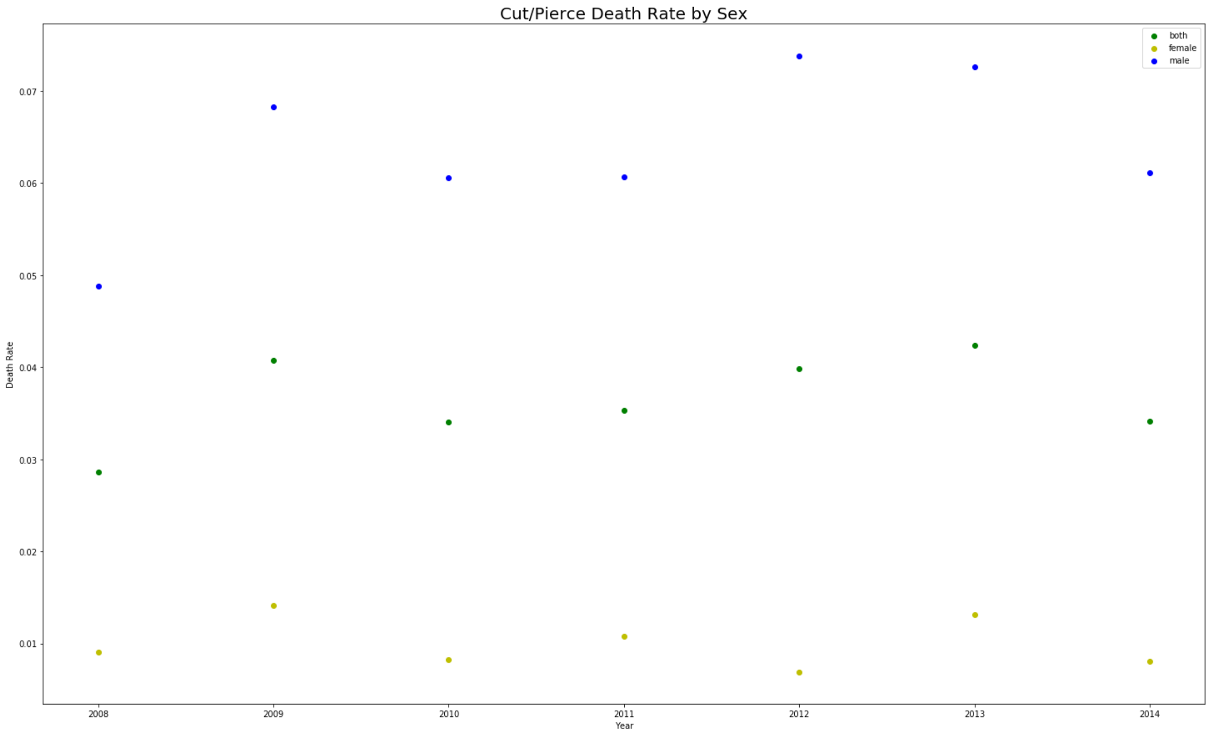


Graph with annual death rate

In [99]:
```
x = cp_both['Year']

y_both = cp_both['Age Specific Rate']
y_f = cp_f['Age Specific Rate']
y_m = cp_m['Age Specific Rate']

plt.figure(figsize=(25,15))
plt.ylabel('Death Rate')
plt.xlabel('Year')

plt.scatter(x, y_both, color = 'g', label = 'both')
plt.scatter(x, y_f, color = 'y', label = 'female')
plt.scatter(x, y_m, color = 'b', label = 'male')
```

```
plt.title("Cut/Pierce Death Rate by Sex", fontsize = 20)
plt.legend()
```

Out[99]: <matplotlib.legend.Legend at 0x1a228e3b50>



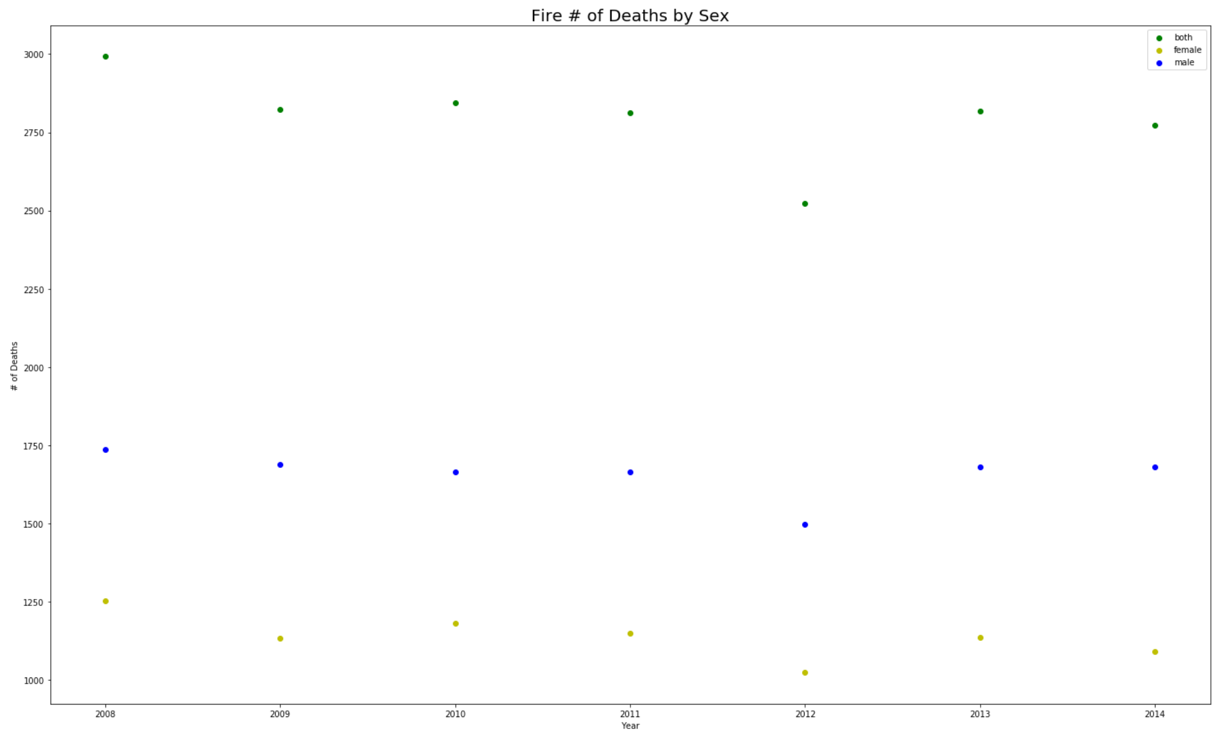
Fire/hot object or substance

In [100]:
```
fire = all_age_race.loc[all_age_race['Injury Mechanism'] == 'Fire/hot o
bject or substance']
fire = fire.sort_values('Year')
fire_both = fire.loc[fire['Sex'] == 'Both sexes']
fire_f = fire.loc[fire['Sex'] == 'Female']
fire_m = fire.loc[fire['Sex'] == 'Male']
```

Graph with number of deaths annually

In [101]:
```python
x = fire_both['Year']

y_both = fire_both['Deaths']
y_f = fire_f['Deaths']
y_m = fire_m['Deaths']

plt.figure(figsize=(25,15))
plt.ylabel('# of Deaths')
plt.xlabel('Year')

plt.scatter(x, y_both, color = 'g', label = 'both')
plt.scatter(x, y_f, color = 'y', label = 'female')
plt.scatter(x, y_m, color = 'b', label = 'male')
plt.title("Fire # of Deaths by Sex", fontsize = 20)
plt.legend()
```

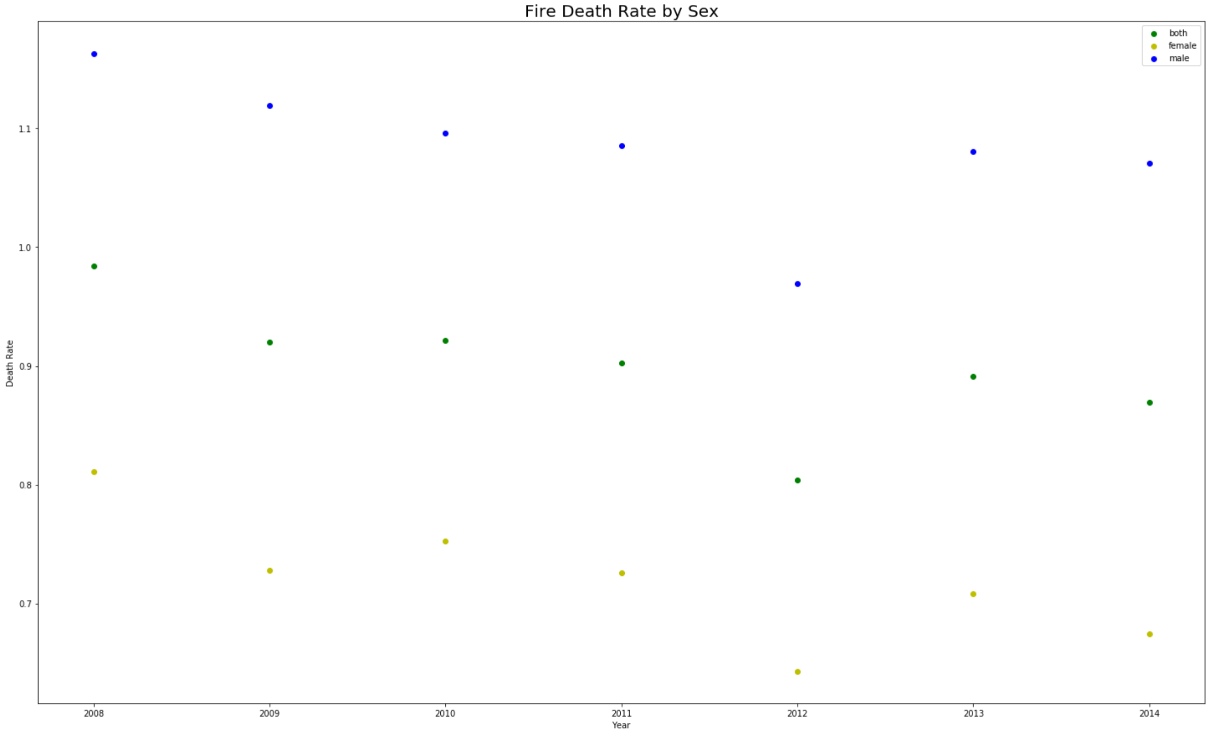
Out[101]:
```
<matplotlib.legend.Legend at 0x1a240c3bd0>
```



Graph with annual death rate

In [102]:
```
x = fire_both['Year']

y_both = fire_both['Age Specific Rate']
y_f = fire_f['Age Specific Rate']
y_m = fire_m['Age Specific Rate']

plt.figure(figsize=(25,15))
plt.ylabel('Death Rate')
plt.xlabel('Year')

plt.scatter(x, y_both, color = 'g', label = 'both')
plt.scatter(x, y_f, color = 'y', label = 'female')
plt.scatter(x, y_m, color = 'b', label = 'male')
plt.title("Fire Death Rate by Sex", fontsize = 20)
plt.legend()
```

Out[102]:
```
<matplotlib.legend.Legend at 0x1a21d09910>
```



Motor vehicle traffic

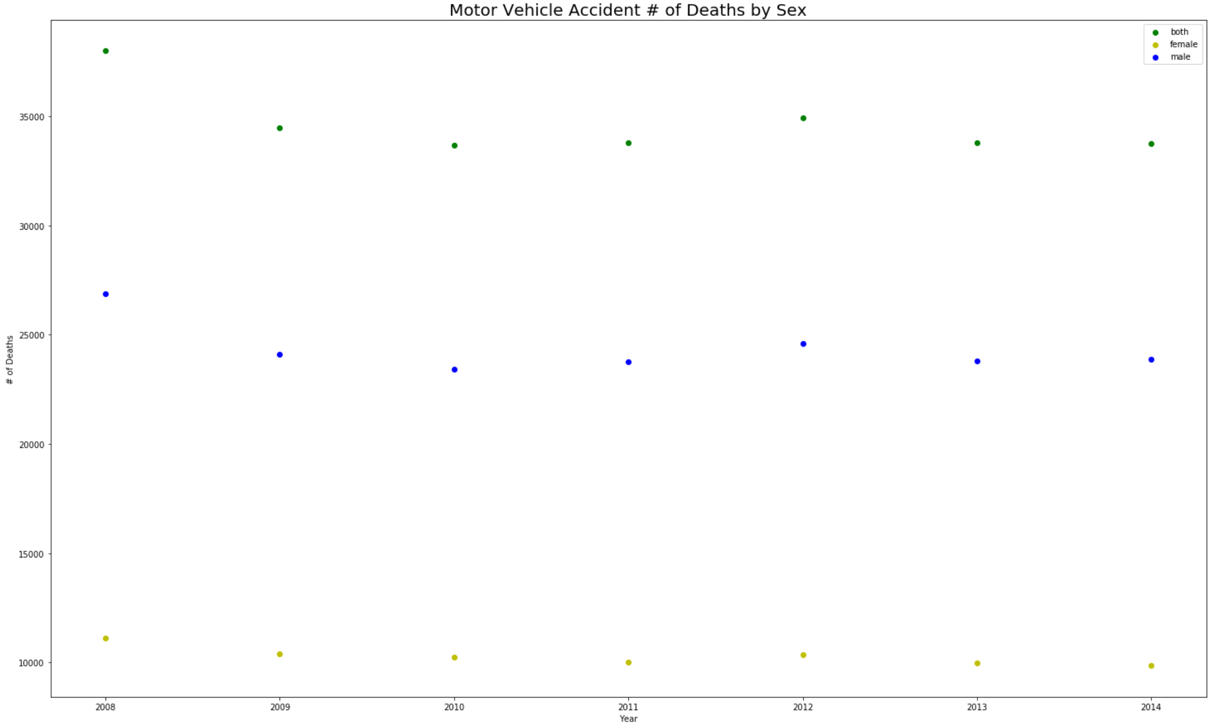
In [103]:
```
m = all_age_race.loc[all_age_race['Injury Mechanism'] == 'Motor vehicle
 traffic']
m = m.sort_values('Year')
m_both = m.loc[m['Sex'] == 'Both sexes']
m_f = m.loc[m['Sex'] == 'Female']
m_m = m.loc[m['Sex'] == 'Male']
```

Graph with number of deaths annually

In [104]:
```
x = m_both['Year']

y_both = m_both['Deaths']
```

```python
y_f = m_f['Deaths']
y_m = m_m['Deaths']

plt.figure(figsize=(25,15))
plt.ylabel('# of Deaths')
plt.xlabel('Year')

plt.scatter(x, y_both, color = 'g', label = 'both')
plt.scatter(x, y_f, color = 'y', label = 'female')
plt.scatter(x, y_m, color = 'b', label = 'male')
plt.title("Motor Vehicle Accident # of Deaths by Sex", fontsize = 20)
plt.legend()
```

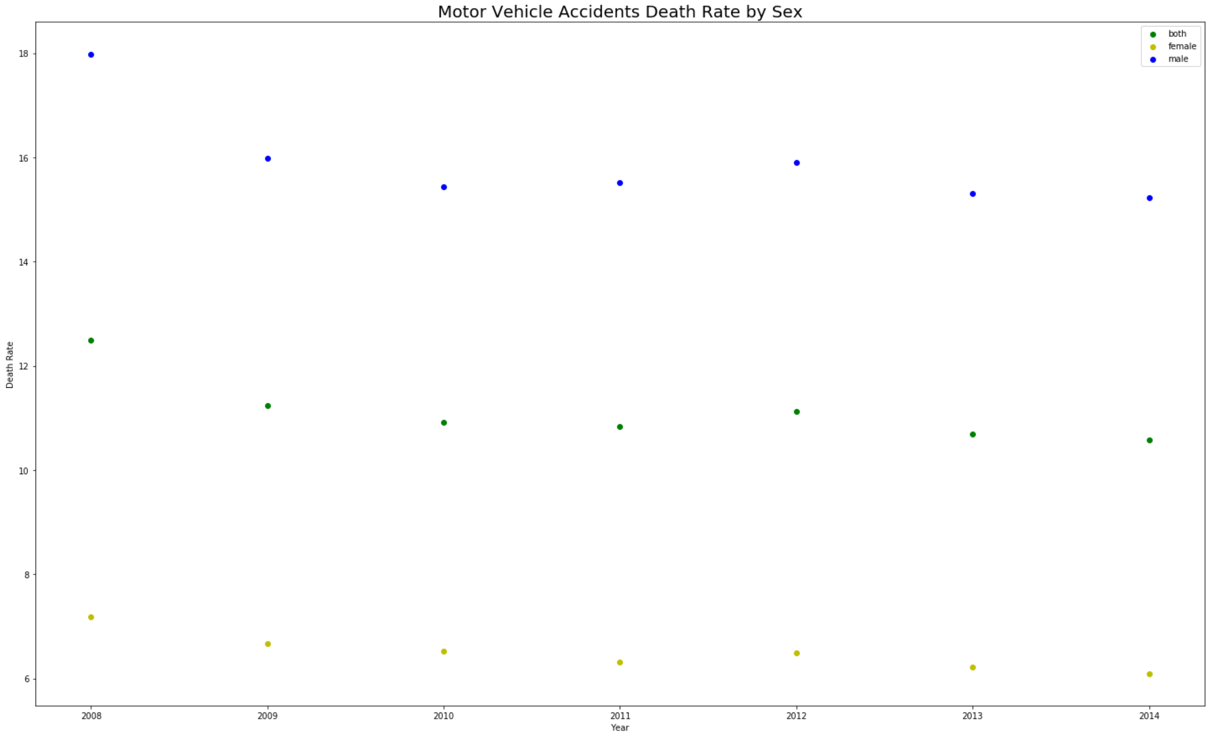
Out[104]: <matplotlib.legend.Legend at 0x1a21119550>



Graph with annual death rate

In [105]:
```
x = m_both['Year']

y_both = m_both['Age Specific Rate']
y_f = m_f['Age Specific Rate']
y_m = m_m['Age Specific Rate']

plt.figure(figsize=(25,15))
plt.ylabel('Death Rate')
plt.xlabel('Year')

plt.scatter(x, y_both, color = 'g', label = 'both')
plt.scatter(x, y_f, color = 'y', label = 'female')
plt.scatter(x, y_m, color = 'b', label = 'male')
plt.title("Motor Vehicle Accidents Death Rate by Sex", fontsize = 20)
plt.legend()
```

Out[105]: <matplotlib.legend.Legend at 0x1a1dd5d3d0>



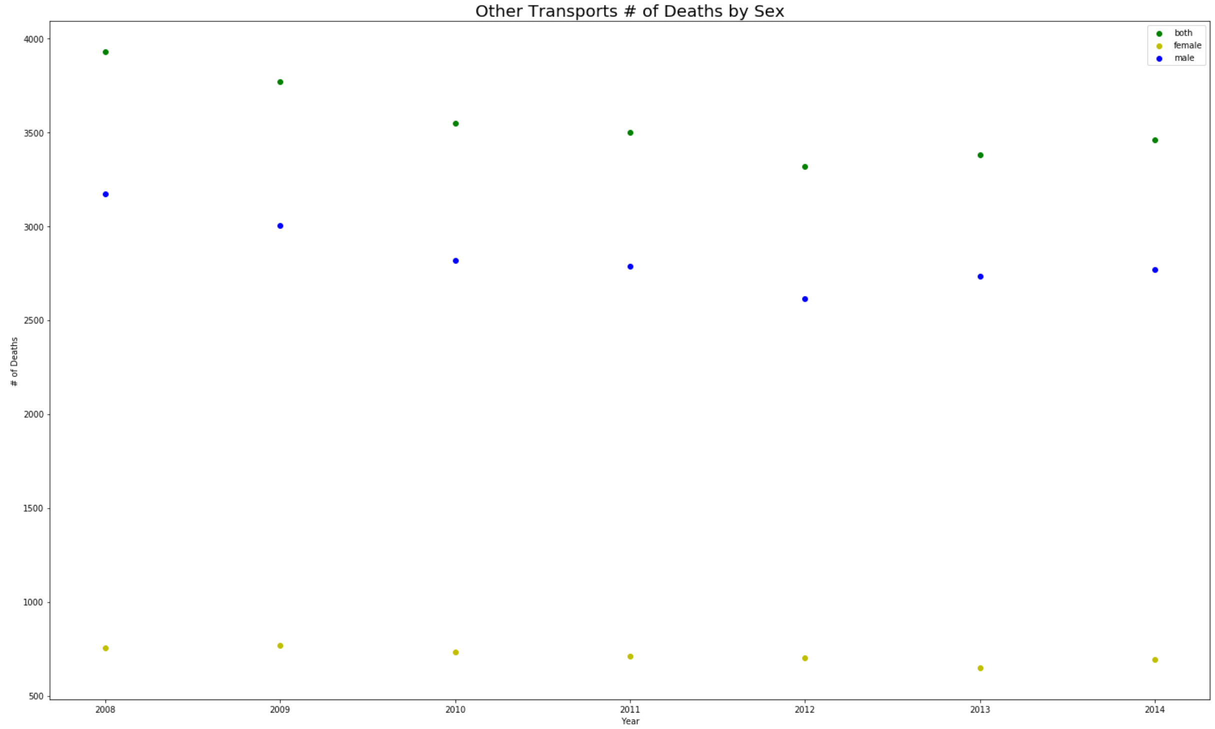
All Other Transport

In [106]:
```
o = all_age_race.loc[all_age_race['Injury Mechanism'] == 'All Other Tra
nsport']
o = o.sort_values('Year')
o_both = o.loc[o['Sex'] == 'Both sexes']
o_f = o.loc[o['Sex'] == 'Female']
o_m = o.loc[o['Sex'] == 'Male']
```

Graph with number of deaths annually

In [107]:
```
x = o_both['Year']

y_both = o_both['Deaths']
y_f = o_f['Deaths']
y_m = o_m['Deaths']

plt.figure(figsize=(25,15))
plt.ylabel('# of Deaths')
plt.xlabel('Year')

plt.scatter(x, y_both, color = 'g', label = 'both')
plt.scatter(x, y_f, color = 'y', label = 'female')
plt.scatter(x, y_m, color = 'b', label = 'male')
plt.title("Other Transports # of Deaths by Sex", fontsize = 20)
plt.legend()
```

Out[107]:
```
<matplotlib.legend.Legend at 0x1a2414c950>
```

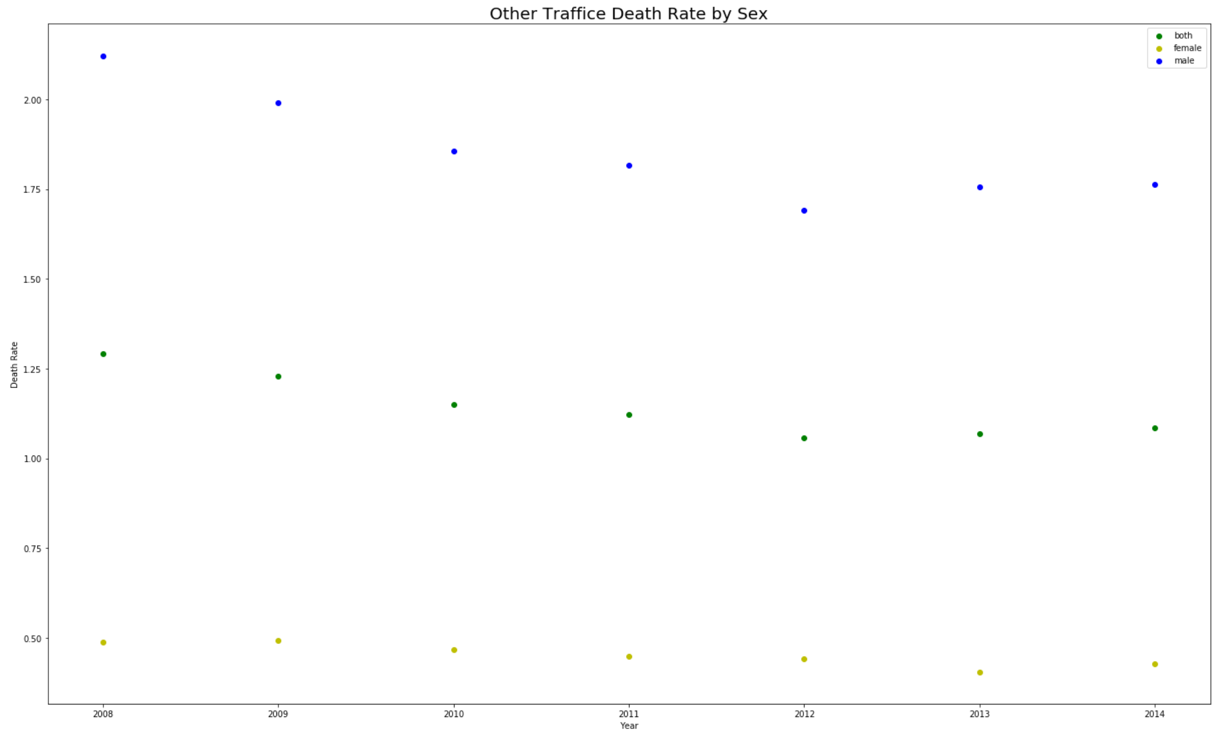


Graph with annual death rate

In [108]:
```
x = o_both['Year']

y_both = o_both['Age Specific Rate']
y_f = o_f['Age Specific Rate']
y_m = o_m['Age Specific Rate']

plt.figure(figsize=(25,15))
plt.ylabel('Death Rate')
plt.xlabel('Year')

plt.scatter(x, y_both, color = 'g', label = 'both')
plt.scatter(x, y_f, color = 'y', label = 'female')
plt.scatter(x, y_m, color = 'b', label = 'male')
```

```
plt.title("Other Traffice Death Rate by Sex", fontsize = 20)
plt.legend()
```

Out[108]: <matplotlib.legend.Legend at 0x1a24410710>



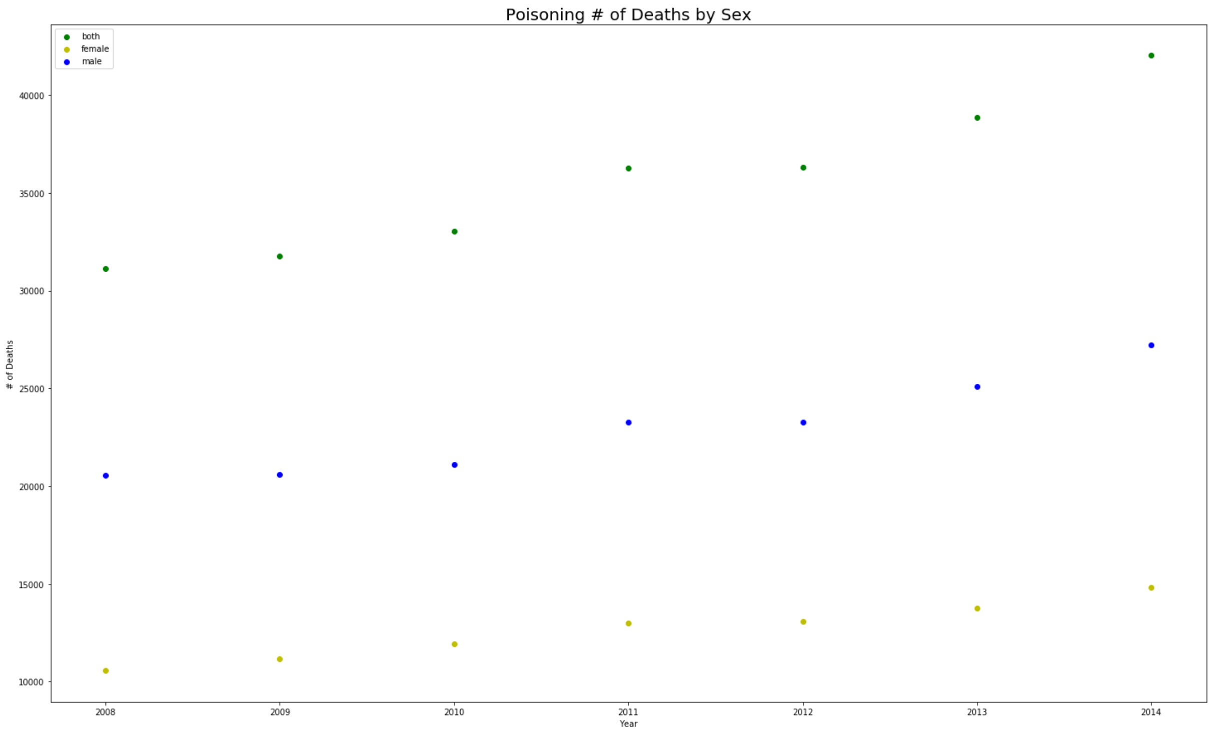
Poisoning

In [109]:
```
p = all_age_race.loc[all_age_race['Injury Mechanism'] == 'Poisoning']
p = p.sort_values('Year')
p_both = p.loc[p['Sex'] == 'Both sexes']
p_f = p.loc[p['Sex'] == 'Female']
p_m = p.loc[p['Sex'] == 'Male']
```

Graph with number of deaths annually

In [110]:
```python
x = p_both['Year']

y_both = p_both['Deaths']
y_f = p_f['Deaths']
y_m = p_m['Deaths']

plt.figure(figsize=(25,15))
plt.ylabel('# of Deaths')
plt.xlabel('Year')

plt.scatter(x, y_both, color = 'g', label = 'both')
plt.scatter(x, y_f, color = 'y', label = 'female')
plt.scatter(x, y_m, color = 'b', label = 'male')
plt.title("Poisoning # of Deaths by Sex", fontsize = 20)
plt.legend()
```

Out[110]: <matplotlib.legend.Legend at 0x1a244d8790>



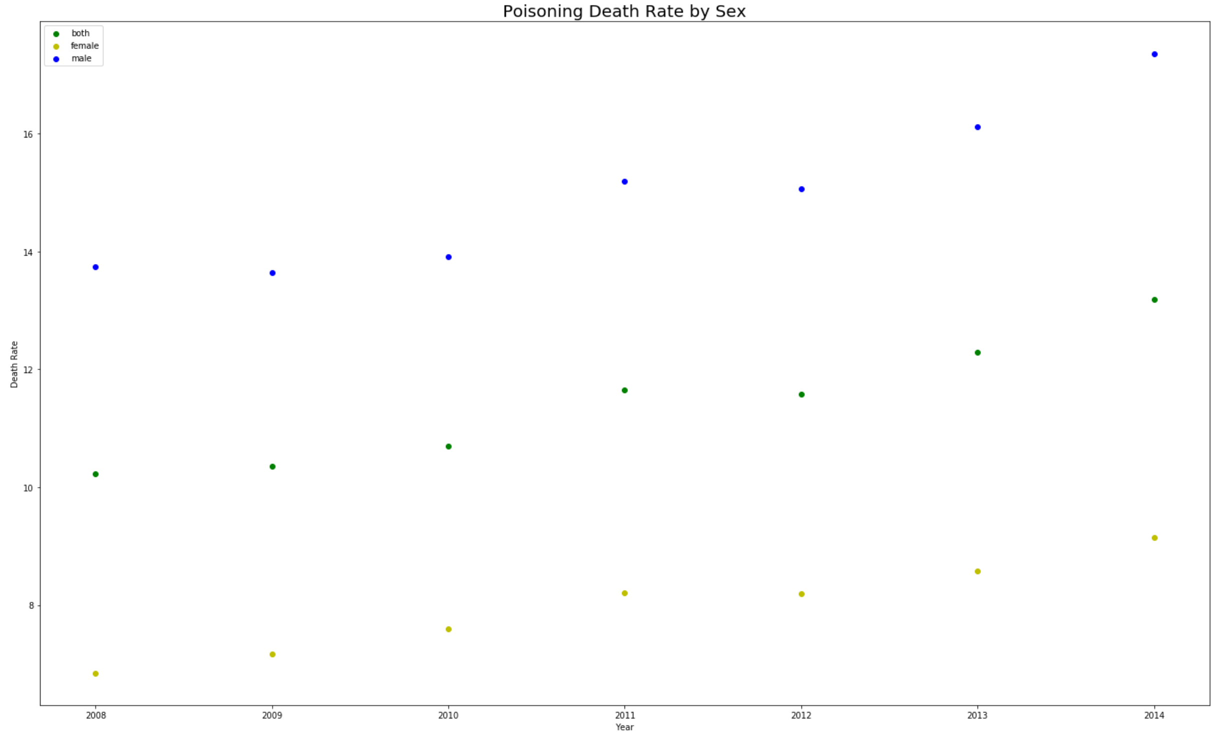
Graph with annual death rate

In [111]:

```
x = p_both['Year']

y_both = p_both['Age Specific Rate']
y_f = p_f['Age Specific Rate']
y_m = p_m['Age Specific Rate']

plt.figure(figsize=(25,15))
plt.ylabel('Death Rate')
plt.xlabel('Year')

plt.scatter(x, y_both, color = 'g', label = 'both')
plt.scatter(x, y_f, color = 'y', label = 'female')
plt.scatter(x, y_m, color = 'b', label = 'male')
plt.title("Poisoning Death Rate by Sex", fontsize = 20)
plt.legend()
```

Out[111]:

```
<matplotlib.legend.Legend at 0x1a24555f50>
```



Suffocation

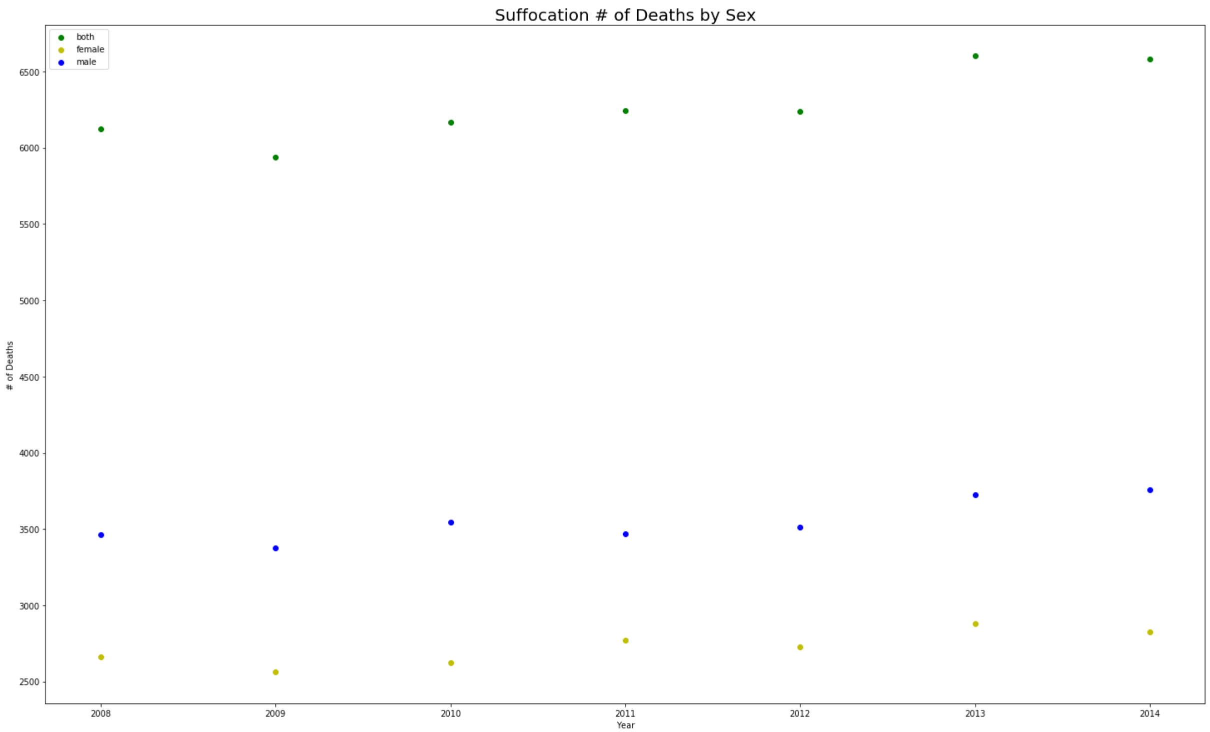
In [112]:
```
s = all_age_race.loc[all_age_race['Injury Mechanism'] == 'Suffocation']
s = s.sort_values('Year')
s_both = s.loc[s['Sex'] == 'Both sexes']
s_f = s.loc[s['Sex'] == 'Female']
s_m = s.loc[s['Sex'] == 'Male']
```

Graph with number of deaths annually

In [113]:
```
x = s_both['Year']

y_both = s_both['Deaths']
y_f = s_f['Deaths']
```

```
y_m = s_m['Deaths']

plt.figure(figsize=(25,15))
plt.ylabel('# of Deaths')
plt.xlabel('Year')

plt.scatter(x, y_both, color = 'g', label = 'both')
plt.scatter(x, y_f, color = 'y', label = 'female')
plt.scatter(x, y_m, color = 'b', label = 'male')
plt.title("Suffocation # of Deaths by Sex", fontsize = 20)
plt.legend()
```

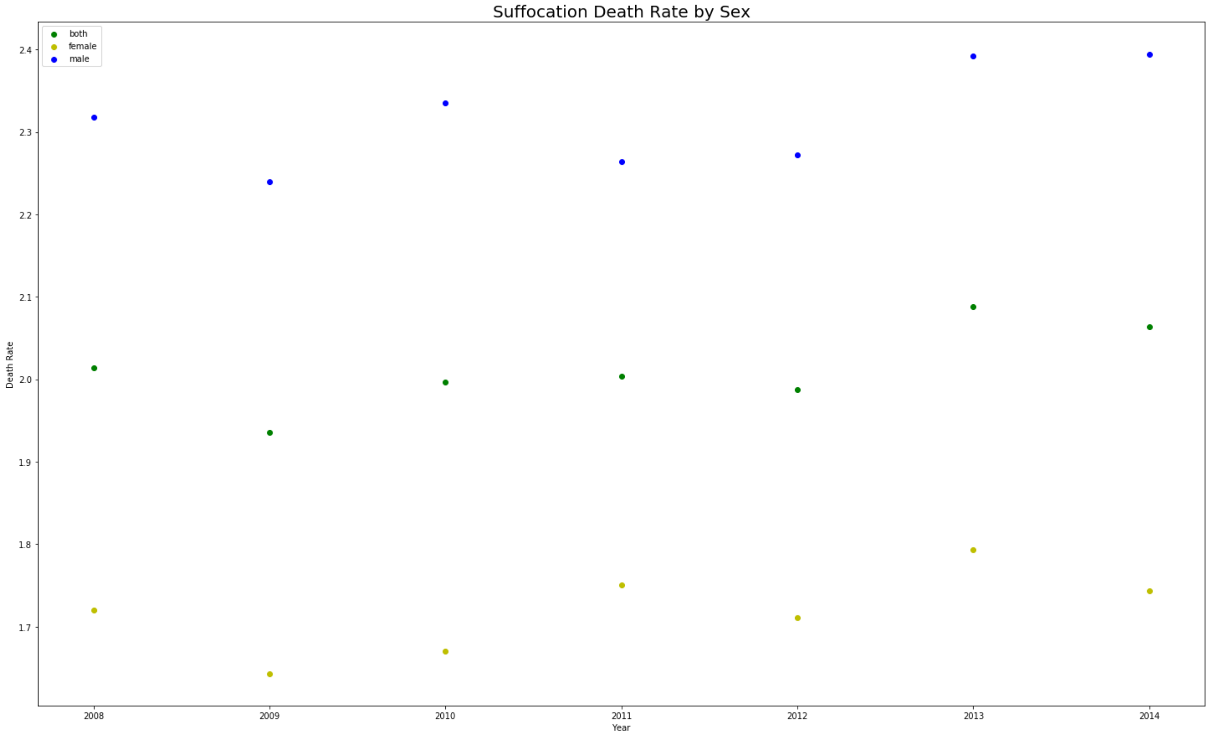
Out[113]: <matplotlib.legend.Legend at 0x1a245e4750>



Graph with annual death rate

In [114]:
```python
x = s_both['Year']

y_both = s_both['Age Specific Rate']
y_f = s_f['Age Specific Rate']
y_m = s_m['Age Specific Rate']

plt.figure(figsize=(25,15))
plt.ylabel('Death Rate')
plt.xlabel('Year')

plt.scatter(x, y_both, color = 'g',label='both')
plt.scatter(x, y_f, color = 'y', label='female')
plt.scatter(x, y_m, color = 'b', label='male')
plt.title("Suffocation Death Rate by Sex",fontsize=20)
plt.legend()
```

Out[114]: <matplotlib.legend.Legend at 0x1a265d5750>



As we can see from the above graphs, the results are quite consistent. Males typically have a higher death rate from each injury mechanism, which makes sense as they have a high death rate when comparing it with all injury mechanisms. However, the only mechanism that fell outside of this pattern was for falls. Females and males had a very close death rater due to falls, which was unique.

In [ ]:

```

```

c. Comparison of Each Mechanism

Comparison of all races, sexes, ages and their annual death rate for each cause of unintentional injury

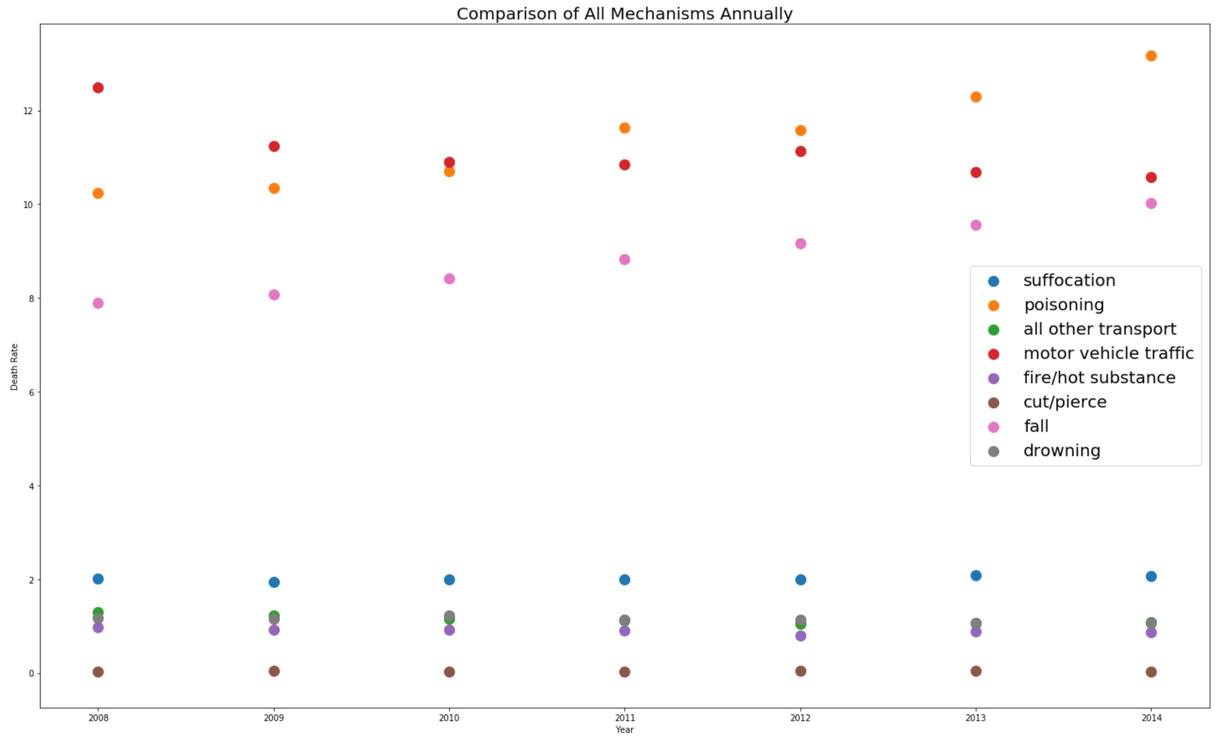
In [115]:

```
labels = s_both['Year']
y_s = s_both['Age Specific Rate'] #suffocation
y_p = p_both['Age Specific Rate'] #poisoning
y_o = o_both['Age Specific Rate'] #all other transport
y_m = m_both['Age Specific Rate'] #motor vehicle traffic
y_fire = fire_both['Age Specific Rate'] #fire/hot object or substance
y_cp = cp_both['Age Specific Rate'] #cut/pierce
y_fa = fa_both['Age Specific Rate'] #firearm
y_fall = fall_both['Age Specific Rate'] #fall
y_drown = drown_both['Age Specific Rate'] #drown
```

In [116]:

```
plt.figure(figsize=(25,15))
plt.scatter(labels, y_s, s=150, label = 'suffocation')
plt.scatter(labels, y_p, s=150, label = 'poisoning')
plt.scatter(labels, y_o, s=150, label = 'all other transport')
plt.scatter(labels, y_m, s=150, label = 'motor vehicle traffic')
plt.scatter(labels, y_fire, s=150, label = 'fire/hot substance')
plt.scatter(labels, y_cp, s=150, label = 'cut/pierce')
plt.scatter(labels, y_fall, s=150, label = 'fall')
plt.scatter(labels, y_drown, s=150, label = 'drowning')
plt.legend(loc='right', prop={'size': 20})
```

```
plt.ylabel('Death Rate')
plt.xlabel('Year')
plt.title('Comparison of All Mechanisms Annually', fontsize=20)
plt.show()
```



From our analysis, we can see that poisoning, motor vehicle traffic, and falls make the top 3 highest rates of death for unintentional injuries in the US. In poisoning and falls, we can see that the rates are steadily increasing with each year. Meanwhile, the rate for death by moter vehicle transport is decreasing across this time frame. The other 5 mechanisms are significantly lower in death rate and are constant across the interval.

d. Regression

In [117]:
```
import statsmodels.formula.api as smf
```

First, a multiple regression where we examine the factors of Age Group, Sex, and Race

In [118]:
```
reg = smf.ols('Q("Age Specific Rate") ~ Q("Age Group (Years)") + Sex +
 Race',mech).fit()
print(reg.summary())
```

```
                              OLS Regression Results

========================================================================
===========
Dep. Variable:     Q("Age Specific Rate")   R-squared:
      0.898
Model:                                OLS   Adj. R-squared:
      0.896
Method:                     Least Squares   F-statistic:
      462.8
Date:                    Wed, 13 May 2020   Prob (F-statistic):
  1.62e-277
Time:                            20:04:57   Log-Likelihood:
    -2415.3
No. Observations:                     588   AIC:
      4855.
Df Residuals:                         576   BIC:
      4907.
Df Model:                              11

Covariance Type:                nonrobust

========================================================================
===============================
                                        coef    std err          t
  P>|t|      [0.025      0.975]
------------------------------------------------------------------------
-------------------------------
Intercept                            31.7009      2.124     14.927
  0.000      27.530      35.872
Q("Age Group (Years)")[T.25–44]       8.6248      2.294      3.760
  0.000       4.119      13.130
```

```
Q("Age Group (Years)")[T.45–64]       15.7852       2.294       6.881
  0.000      11.280      20.291
Q("Age Group (Years)")[T.65–74]       16.9988       2.294       7.410
  0.000      12.493      21.504
Q("Age Group (Years)")[T.75+]        118.3837       2.294      51.608
  0.000     113.878     122.889
Q("Age Group (Years)")[T.< 15]       -18.5772       2.294      -8.099
  0.000     -23.083     -14.072
Q("Age Group (Years)")[T.All Ages]     9.7909       2.294       4.268
  0.000       5.285      14.296
Sex[T.Female]                        -12.8072       1.502      -8.528
  0.000     -15.757      -9.858
Sex[T.Male]                           14.9320       1.502       9.943
  0.000      11.982      17.881
Race[T.Hispanic]                     -19.1519       1.734     -11.045
  0.000     -22.558     -15.746
Race[T.Non-Hispanic black]           -12.5577       1.734      -7.242
  0.000     -15.963      -9.152
Race[T.Non-Hispanic white]             5.7817       1.734       3.334
  0.001       2.376       9.187
=======================================================================
=======
Omnibus:                      42.813   Durbin-Watson:
  1.960
Prob(Omnibus):                 0.000   Jarque-Bera (JB):
185.118
Skew:                          0.013   Prob(JB):
6.34e-41
Kurtosis:                      5.749   Cond. No.
   9.34
=======================================================================
=======

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

Next, a regression where we examine the effects of Age Group and Sex.

In [119]:
```python
reg = smf.ols('Q("Age Specific Rate") ~ Q("Age Group (Years)") + Sex',r
ace_mech).fit()
print(reg.summary())
```

```
                            OLS Regression Results                            
==============================================================================
===========
Dep. Variable:     Q("Age Specific Rate")   R-squared:                       
      0.989
Model:                                OLS   Adj. R-squared:                  
      0.988
Method:                     Least Squares   F-statistic:                     
      1509.
Date:                    Wed, 13 May 2020   Prob (F-statistic):             
  2.65e-130
Time:                            20:04:57   Log-Likelihood:                 
    -463.44
No. Observations:                     147   AIC:                             
      944.9
Df Residuals:                         138   BIC:                             
      971.8
Df Model:                               8                                    
     
Covariance Type:                nonrobust                                    
     
==============================================================================
===============================
                                      coef    std err          t     
  P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
-------------------------------
Intercept                          27.4866      1.446     19.011     
  0.000      24.628      30.345
Q("Age Group (Years)")[T.25–44]     9.1647      1.803      5.082     
  0.000       5.599      12.730
Q("Age Group (Years)")[T.45–64]    15.4766      1.803      8.583     
  0.000      11.911      19.042
Q("Age Group (Years)")[T.65–74]    16.3885      1.803      9.088     
  0.000      12.823      19.954
```

```
Q("Age Group (Years)")[T.75+]         149.2280      1.803     82.755
  0.000     145.662     152.794
Q("Age Group (Years)")[T.< 15]        -21.2402      1.803    -11.779
  0.000     -24.806     -17.675
Q("Age Group (Years)")[T.All Ages]     12.4854      1.803      6.924
  0.000       8.920      16.051
Sex[T.Female]                         -12.7928      1.181    -10.837
  0.000     -15.127     -10.459
Sex[T.Male]                            14.4907      1.181     12.275
  0.000      12.156      16.825
========================================================================
=======
Omnibus:                       11.847   Durbin-Watson:
  1.837
Prob(Omnibus):                  0.003   Jarque-Bera (JB):
30.060
Skew:                          -0.138   Prob(JB):
2.97e-07
Kurtosis:                       5.198   Cond. No.
   8.70
========================================================================
=======

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

Lastly, a regression where we examine the effects of Age Group

In [120]:

```
reg = smf.ols('Q("Age Specific Rate") ~ Q("Age Group (Years)")',race_se
x_mech).fit()
print(reg.summary())
```

```
                              OLS Regression Results

========================================================================
===========
Dep. Variable:     Q("Age Specific Rate")   R-squared:
```

```
      0.997
Model:                            OLS   Adj. R-squared:
      0.997
Method:                 Least Squares   F-statistic:
      2332.
Date:                Wed, 13 May 2020   Prob (F-statistic):
   2.50e-51
Time:                        20:04:57   Log-Likelihood:
    -119.60
No. Observations:                  49   AIC:
      253.2
Df Residuals:                      42   BIC:
      266.4
Df Model:                           6

Covariance Type:            nonrobust

======================================================================
===============================
                                          coef    std err          t
  P>|t|      [0.025      0.975]
----------------------------------------------------------------------
-------------------------------
Intercept                              28.2649      1.134     24.919
  0.000      25.976      30.554
Q("Age Group (Years)")[T.25–44]         8.9670      1.604      5.590
  0.000       5.730      12.204
Q("Age Group (Years)")[T.45–64]        14.9950      1.604      9.348
  0.000      11.758      18.232
Q("Age Group (Years)")[T.65–74]        15.5099      1.604      9.669
  0.000      12.273      18.747
Q("Age Group (Years)")[T.75+]         145.8634      1.604     90.931
  0.000     142.626     149.101
Q("Age Group (Years)")[T.< 15]        -21.4325      1.604    -13.361
  0.000     -24.670     -18.195
Q("Age Group (Years)")[T.All Ages]     12.1522      1.604      7.576
  0.000       8.915      15.389
======================================================================
=======
Omnibus:                       14.753   Durbin-Watson:
```

```
  1.682
Prob(Omnibus):                  0.001   Jarque-Bera (JB):
50.705
Skew:                          -0.427   Prob(JB):
9.76e-12
Kurtosis:                       7.910   Cond. No.
   7.87
========================================================================
=======

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

Based off of the three regressions, we find that age group gives the highest R squared value of 0.997, indicating that there is a large positive correlation with the death rate of unintentional injury and age.

This could be attributed to factors such as that younger people are typically in better physical health, which assists them in recovering, or that younger people are less likely to have pre-existing conditions that may make one more likely to sustain injuries. However, this is all speculation, more research must be done in these areas.

e. NYC Unintentional Injuries

As seen in the analysis for the US, the top 3 unintentional injury mechanisms are poisoning, motor vehicle accidents, and falls. Now, we would like to examine these 3 mechanisms in the scope of New York City.

ui_deaths is a dataset of the number of deaths from 2012 to 2014 in NYC for the poisoning, motor vehicle accidents, and falls.

ui_hos is a dataset of the number of hospitalizations from 2012 to 2014 in NYC for poisoning, motor vehicle accidents, and falls.

Source: https://www1.nyc.gov/site/doh/data/data-sets/injury.page

In [121]:
```
ui_deaths = pd.read_csv("nyc_u_injury_death.csv")
ui_deaths
```

Out[121]:

	Age Group	Motor Vehicle Accident	Poisoning	Fall
0	<1	NaN	NaN	NaN
1	1-4	NaN	NaN	NaN
2	5-9	NaN	NaN	NaN
3	10-14	1	NaN	NaN
4	15-24	4	4	NaN
5	25-34	3	10	NaN
6	35-44	3	14	2
7	45-54	3	21	3
8	55-64	4	16	5
9	65+	8	3	27

In [122]:
```
ui_deaths.dtypes
```

Out[122]:
```
Age Group                 object
Motor Vehicle Accident    object
Poisoning                 object
Fall                      object
dtype: object
```

In [123]:
```
ui_deaths = ui_deaths.astype({'Motor Vehicle Accident': 'float64', 'Poisoning': 'float64', "Fall":"float64"})
ui_deaths.dtypes
```

Out[123]:
```
Age Group                  object
Motor Vehicle Accident    float64
Poisoning                 float64
Fall                      float64
dtype: object
```

In [124]:
```
ui_hos = pd.read_csv("nyc_u_injury_hospitalizations.csv")
ui_hos
```

Out[124]:

	Age Group	Motor Vehicle Accident	Poisoning	Fall
0	<1	NaN	24	188
1	1-4	9	45	115
2	5-9	23	9	101
3	10-14	40	9	79
4	15-24	72	27	69
5	25-34	59	35	86
6	35-44	56	61	124
7	45-54	62	126	240
8	55-64	66	107	401
9	65+	78	84	1690

In [125]:
```
ui_hos.dtypes
```

Out[125]:
```
Age Group                 object
Motor Vehicle Accident    object
Poisoning                  int64
Fall                       int64
dtype: object
```

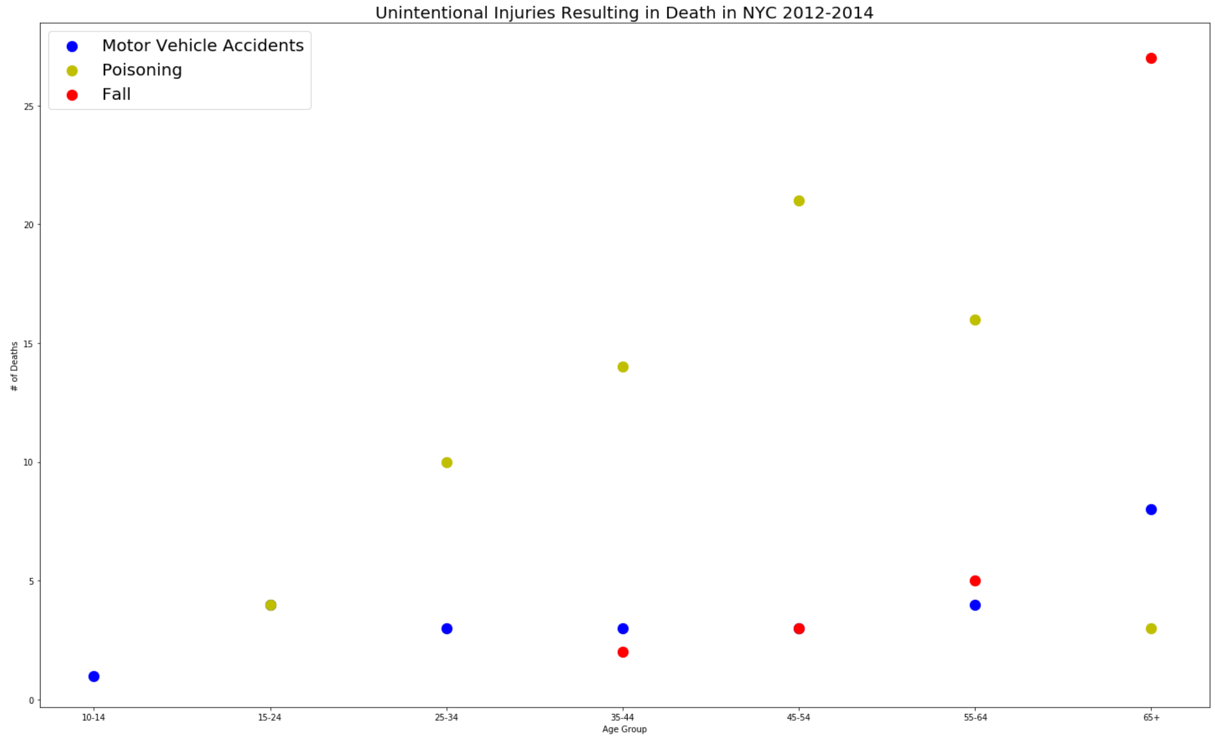
In [126]:
```
ui_hos = ui_hos.astype({'Motor Vehicle Accident': 'float64', 'Poisonin
g': 'float64', "Fall":"float64"})
ui_hos.dtypes
```

Out[126]:
```
Age Group                   object
Motor Vehicle Accident     float64
Poisoning                  float64
Fall                       float64
dtype: object
```

Graphing Unintentional Injuries Resulting in Death in NYC 2012-2014

In [127]:
```
x = ui_deaths['Age Group']

d_mva = ui_deaths['Motor Vehicle Accident']
d_p = ui_deaths['Poisoning']
d_f = ui_deaths['Fall']

plt.figure(figsize=(25,15))
plt.ylabel('# of Deaths')
plt.xlabel('Age Group')
plt.title('Unintentional Injuries Resulting in Death in NYC 2012-2014',
 fontsize=20)

plt.scatter(x, d_mva, s=150, label = 'Motor Vehicle Accidents', color =
 'b')
plt.scatter(x, d_p, s=150, label = 'Poisoning', color = 'y')
plt.scatter(x, d_f, s=150, label = 'Fall', color = 'r')
plt.legend(loc='upper left', prop={'size': 20})
```

Out[127]:
```
<matplotlib.legend.Legend at 0x1a20356090>
```



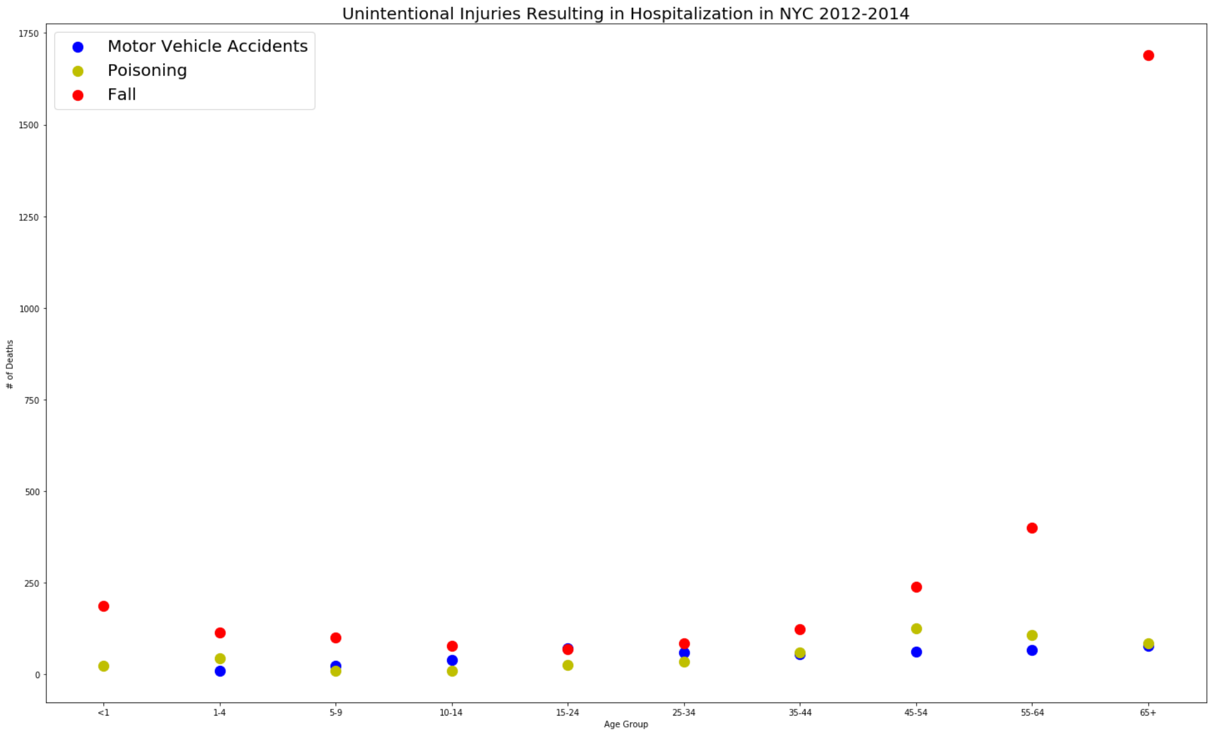
Graphing Unintentional Injuries Resulting in Hospitalization in NYC 2012-2014

In [128]:
```
x = ui_hos['Age Group']

h_mva = ui_hos['Motor Vehicle Accident']
h_p = ui_hos['Poisoning']
h_f = ui_hos['Fall']

plt.figure(figsize=(25,15))
plt.ylabel('# of Deaths')
plt.xlabel('Age Group')
plt.title('Unintentional Injuries Resulting in Hospitalization in NYC 2
012-2014', fontsize=20)
```

```
plt.scatter(x, h_mva, s=150, label = 'Motor Vehicle Accidents', color =
 'b')
plt.scatter(x, h_p, s=150, label = 'Poisoning', color = 'y')
plt.scatter(x, h_f, s=150, label = 'Fall', color = 'r')
plt.legend(loc='upper left', prop={'size': 20})
plt.legend(fontsize=20)
```

Out[128]:

```
<matplotlib.legend.Legend at 0x1a266c1c10>
```



In [129]:

```
mva_drate = round(((d_mva.sum())/(h_mva.sum()))*100,2)
p_drate = round(((d_p.sum())/(h_p.sum()))*100,2)
f_drate = round(((d_f.sum())/(h_f.sum()))*100,2)
```

In [130]:

```
print('These are the death rates for these hospitalized unintentional i
njuries from these 2 datasets in NYC for 2012-2014:')
print('Motor Vehicle Accidents:', str(mva_drate))
```

```
print('Poisoning:', str(p_drate))
print('Fall:', str(f_drate))
```

```
These are the death rates for these hospitalized unintentional injuries
from these 2 datasets in NYC for 2012-2014:
Motor Vehicle Accidents: 5.59
Poisoning: 12.9
Fall: 1.2
```

In [131]:
```
m_both = m_both.loc[m_both['Year'] >=2012]
us_m = m_both['Age Specific Rate'].mean()

p_both = p_both.loc[p_both['Year'] >=2012]
us_p = p_both['Age Specific Rate'].mean()

fa_both = fa_both.loc[fa_both['Year'] >=2012]
us_fa = fa_both['Age Specific Rate'].mean()
```

In [132]:
```
print('These are the death rates for these unintentional injuries in th
e US for 2012-2014:')
print('Motor Vehicle Accidents:', str(round(us_m, 2)))
print('Poisoning:', str(round(us_p, 2)))
print('Fall:', str(round(us_fa, 2)))
```

```
These are the death rates for these unintentional injuries in the US fo
r 2012-2014:
Motor Vehicle Accidents: 10.8
Poisoning: 12.35
Fall: 0.16
```

As we can see from the analysis, NYC has a similar death rate for accidental poisoning. However, NYC has a 50% lower death rate from motor vehicle accidents compared to that of the US, while NYC has about a 7 times higher death rate due to falls compared to the US.

We can interpret this through the fact that NYC is a densely populated area. The lack of square footage means that buildings must grow vertically and that streets are narrow and filled with slow moving cars. Cars must move slowly as there are numerous pedestrians, bicyclists, and traffic lights, along with the 25 mph speed limit. This could be why NYC has a significantly lower death rate for motor vehicle accidents, because even though these accidents do occur, they are not as severe due to the slower speeds vehicles must travel at in the city.

Meanwhile, the higher rate for falls is also unsurprising. NYC requires far more walking, which increases the risk of people tripping and falling on uneven sidewalks or in the plentiful construction zones in the city. Additionally, buildings in NYC are notoriously tall, with many apartment buildings lacking elevators, so falling simply from stairs is highly likely as well.

Another factor to consider is the proximity in NYC. Unlike other areas of the US, NYC is always full of people, which means that if someone is injured there is a high chance that there are witnesses who can help get the victim help quickly. That quick action could mean life saving differences.

If we look at New York State and compare its injury deaths with the US, we find that NY is actually the healthiest state in this aspect with the lowest deaths due to injury per 100,000 population. This could be attributed to several factors, such as having a low obesity rate and a high rate of primary care physicians. These factors would help explain NYC's situation as well. Because people walk frequently in New York, this could contribute to the lower obesity rates. Meanwhile, anyone in New York City could tell you about the neverending sound of sirens, and this is partially due to the numerous physicians found throughout the city.

Source:
https://www.americashealthrankings.org/explore/annual/measure/injury_deaths/state/NY?edition-year=2019

In [ ]:

```

```

4. Conclusions on Death Rate Disparities between New York City and National Averages

After analyzing these three causes of death, we found that NYC's differences cannot be fully explained by the tests here. In the case of heart disease, we dismissed this as statistical variance as the data suggests this.

In regards to influenza & pneumonia death rates, New Yorkers are at a higher risk to die from the flu. We have seen a combination of the city's density, as well as the amount of hospitals and urgent care units predict as much. One thing the city can do is build urgent care units (as these were stronger predictors than hospitals) in neighborhoods or areas that are hit the hardest by the virus. The disparity of deaths from the flu in New York City compared to the rest of the country is significnat, and neccessary measures can be taken to lower these needless deaths.

Meanwhile for unintentional injuries, NYC is seen to have a varying rates compared to the national mean. This could be attributed to the unique characteristics of NYC, such as being densely populated in such a small area, making motor vehicle accidents less fatal while also making falls significantly more fatal. However, there would have to be much more research conducted to reach a conclusive result.

In [ ]:

III. Effect of Race and Gender on Death Rates

In [133]:

```
# prepare data for visualization
# get number of deaths by cause and gender
nyc_gender = nyc.dropna().groupby(['Leading Cause','Year','Sex'],as_ind
ex=False)['Deaths'].sum()

#target years 2008 - 2014
nyc_gender = nyc_gender.loc[nyc_gender['Year']>2007]
nyc_gender
```

Out[133]:

	Leading Cause	Year	Sex	Deaths
1	Alzheimer's disease	2008	F	151.0
2	Alzheimer's disease	2009	F	354.0
3	Alzheimer's disease	2010	F	406.0

	Leading Cause	Year	Sex	Deaths
4	Alzheimer's disease	2011	F	435.0
5	Alzheimer's disease	2012	F	463.0
...	...	...	...	...
140	Unintentional injuries	2012	M	701.0
141	Unintentional injuries	2013	F	261.0
142	Unintentional injuries	2013	M	687.0
143	Unintentional injuries	2014	F	281.0
144	Unintentional injuries	2014	M	662.0

127 rows × 4 columns

In [134]:

```
idx = nyc_pop_00_10.loc[nyc_pop_00_10["NAME"] == "New York city"].index
[0]

# map years to population
nyc_pop = {
    #2007: nyc_pop_00_10["POPESTIMATE2007"][idx],
    2008: nyc_pop_00_10["POPESTIMATE2008"][idx],
    2009: nyc_pop_00_10["POPESTIMATE2009"][idx],
    2010: nyc_pop_00_10["CENSUS2010POP"][idx],
    2011: int(nyc_pop_10_18["respop72011"][1]),
    2012: int(nyc_pop_10_18["respop72012"][1]),
    2013: int(nyc_pop_10_18["respop72013"][1]),
    2014: int(nyc_pop_10_18["respop72014"][1])
}

# get per 1000 quotient
quotient = nyc_pop;
for key in nyc_pop.keys():
    quotient[key] = nyc_pop[key]/1000

quotient
```

Out[134]:

```
{2008: 8068.195,
```

```
 2009: 8131.574,
 2010: 8175.133,
 2011: 8272.963,
 2012: 8348.032,
 2013: 8398.739,
 2014: 8437.387}
```

In [135]:

```python
# calculate deaths per 1000 people
per1000 = [];
for index, row in nyc_gender.iterrows():
    q = quotient.get(row['Year'])
    per1000.append(row['Deaths']/q)
nyc_gender['per1000'] = per1000

nyc_gender
```

Out[135]:

	Leading Cause	Year	Sex	Deaths	per1000
1	Alzheimer's disease	2008	F	151.0	0.018715
2	Alzheimer's disease	2009	F	354.0	0.043534
3	Alzheimer's disease	2010	F	406.0	0.049663
4	Alzheimer's disease	2011	F	435.0	0.052581
5	Alzheimer's disease	2012	F	463.0	0.055462
...	...	...	...	...	...
140	Unintentional injuries	2012	M	701.0	0.083972
141	Unintentional injuries	2013	F	261.0	0.031076
142	Unintentional injuries	2013	M	687.0	0.081798
143	Unintentional injuries	2014	F	281.0	0.033304
144	Unintentional injuries	2014	M	662.0	0.078460

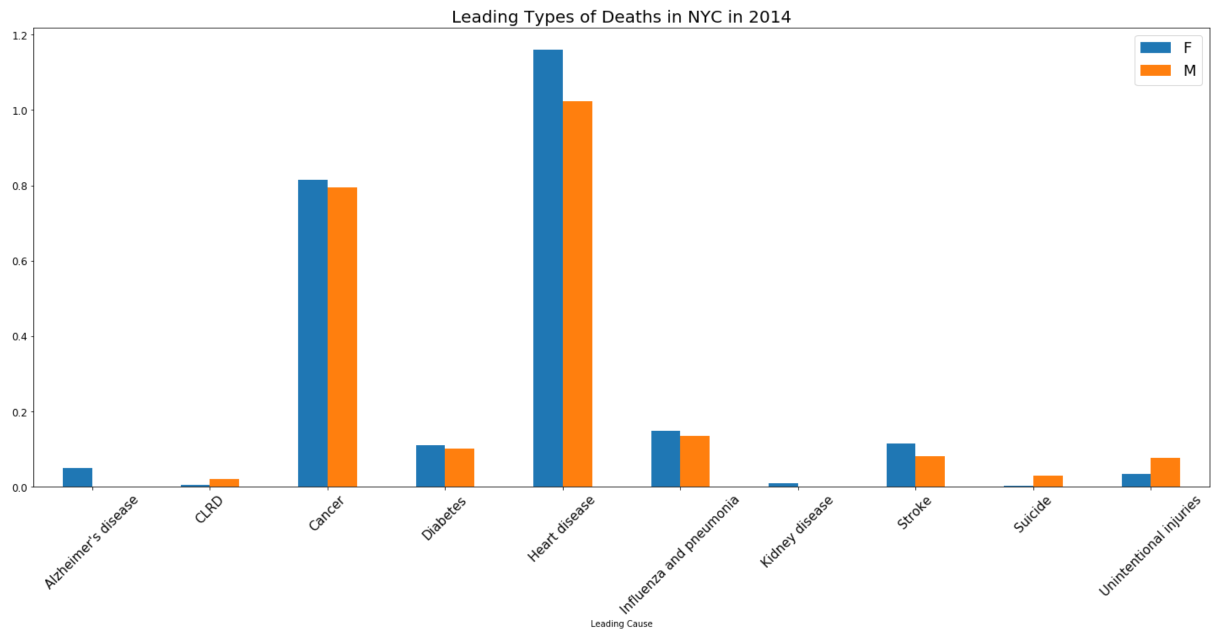
127 rows × 5 columns

1. NYC Visualization of Death by Gender

In [136]:
```
nyc_2014 = nyc_gender.loc[nyc_gender['Year']==2014,:].set_index('Leadin
g Cause')
```

In [137]:
```
fig,ax = plt.subplots()
nyc_gender.pivot_table(values='per1000',index='Leading Cause',columns=
'Sex').plot.bar(ax=ax, figsize=(25,10))
ax.set_title("Leading Types of Deaths in NYC in 2014", size = 20)
ax.tick_params(axis='y', which='major', labelsize=12)
ax.tick_params(axis='x', which='major', labelsize=15, rotation=45)
ax.legend(prop=dict(size=18))
```

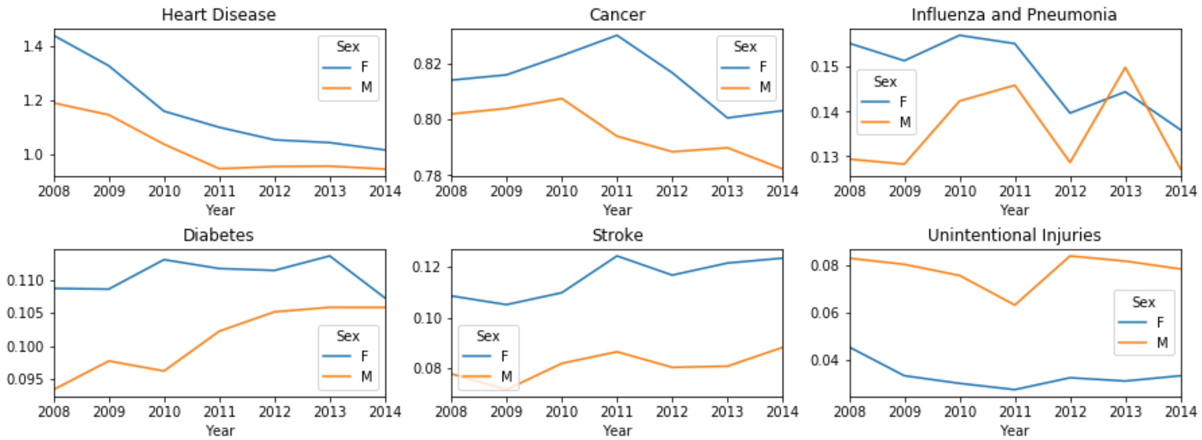
Out[137]: <matplotlib.legend.Legend at 0x1a2043b2d0>



In [138]:
```
fig,ax = plt.subplots(nrows=2, ncols=3, figsize=(15,5))
fig.subplots_adjust(hspace=0.5, wspace=0.2)
cause_gender = nyc_gender.pivot_table(values='per1000',index='Year',col
umns=['Leading Cause','Sex'])
```

```
cause_gender.plot(y='Heart disease', ax=ax[0][0], title='Heart Disease'
)
cause_gender.plot(y='Cancer', ax=ax[0][1], title='Cancer')
cause_gender.plot(y='Influenza and pneumonia', ax=ax[0][2], title='Infl
uenza and Pneumonia')
cause_gender.plot(y='Diabetes', ax=ax[1][0], title='Diabetes')
cause_gender.plot(y='Stroke', ax=ax[1][1], title='Stroke')
cause_gender.plot(y='Unintentional injuries', ax=ax[1][2], title='Unint
entional Injuries')
```

Out[138]: <matplotlib.axes._subplots.AxesSubplot at 0x1a2682e0d0>



2. NYC Race Demographics

In [139]:
```
nyc['Race Ethnicity'].unique()
```

Out[139]:
```
array(['Hispanic', 'White Non-Hispanic', 'Asian and Pacific Islander',
       'Other Race/ Ethnicity', 'Black Non-Hispanic',
       'Not Stated/Unknown'], dtype=object)
```

In [140]:
```
# nyc population dataset for 2010
nyc_pop = pd.read_excel('nyc_census.xlsx', encoding='latin-1').loc[pd.n
p.r_[121:123, 130:138]].drop(['Unnamed: 1','Unnamed: 4','Unnamed: 5','U
nnamed: 6'],axis=1)
```

```
nyc_pop = nyc_pop.rename(columns={'DP-1 - New York City, New York: Prof
ile of General Population and Housing Characteristics: 2010':'Subject:
 2010','Unnamed: 2':'Population','Unnamed: 3':'Percent'})
nyc_pop = nyc_pop.astype({'Subject: 2010':str, 'Population':int, 'Perce
nt':int})
nyc_pop
```

Out[140]:

	Subject: 2010	Population	Percent
121	Total population	8175133	100
122	Hispanic or Latino	2336076	28
130	Not Hispanic or Latino	5839057	71
131	White alone	2722904	33
132	Black or African American alone	1861295	22
133	American Indian and Alaska Native alone	17427	0
134	Asian alone	1028119	12
135	Native Hawaiian and Other Pacific Island...	2795	0
136	Some Other Race alone	57841	0
137	Two or More Races	148676	1

In [141]:

```
nyc_pop_10 = {
    'Hispanic': nyc_pop.loc[122]['Population'],
    'White Non-Hispanic': nyc_pop.loc[131]['Population'],
    'Asian and Pacific Islander': nyc_pop.loc[134]['Population'] + nyc_
pop.loc[135]['Population'],
    'Black Non-Hispanic': nyc_pop.loc[132]['Population'],
    'Other Race/ Ethnicity': nyc_pop.loc[133]['Population'] + nyc_pop.l
oc[136]['Population']
}

nyc_pop_10
```

Out[141]:

```
{'Hispanic': 2336076,
 'White Non-Hispanic': 2722904,
```

```
'Asian and Pacific Islander': 1030914,
'Black Non-Hispanic': 1861295,
'Other Race/ Ethnicity': 75268}
```

3. NYC Visualization by Race Ethnicity

In [142]:
```
nyc_race = nyc.dropna().groupby(['Leading Cause','Year','Race Ethnicit
y'],as_index=False)['Deaths'].sum()
nyc_race
```

Out[142]:

	Leading Cause	Year	Race Ethnicity	Deaths
0	Alzheimer's disease	2007	Not Stated/Unknown	0.0
1	Alzheimer's disease	2007	White Non-Hispanic	107.0
2	Alzheimer's disease	2008	White Non-Hispanic	151.0
3	Alzheimer's disease	2009	Asian and Pacific Islander	14.0
4	Alzheimer's disease	2009	Black Non-Hispanic	79.0
...	...	...	...	...
380	Unintentional injuries	2014	Black Non-Hispanic	148.0
381	Unintentional injuries	2014	Hispanic	240.0
382	Unintentional injuries	2014	Not Stated/Unknown	0.0
383	Unintentional injuries	2014	Other Race/ Ethnicity	18.0
384	Unintentional injuries	2014	White Non-Hispanic	427.0

385 rows × 4 columns

In [143]:
```
#remove Not Stated/Unknown
nyc_race = nyc_race.set_index('Race Ethnicity').drop(index='Not Stated/
Unknown').reset_index()
```

In [144]:
```
nyc_race_2010 = nyc_race.loc[nyc_race['Year']==2010,:].set_index('Leadi
```

```
ng Cause')


ratio = []
for index, row in nyc_race_2010.iterrows():
    #population per 1000 quotient
    pop = nyc_pop_10.get(row['Race Ethnicity'])/1000
    ratio.append(row['Deaths']/pop)

nyc_race_2010['ratio'] = ratio

nyc_race_2010
```

Out[144]:

	Race Ethnicity	Year	Deaths	ratio
Leading Cause				
Alzheimer's disease	Black Non-Hispanic	2010	88.0	0.047279
Alzheimer's disease	Hispanic	2010	71.0	0.030393
Alzheimer's disease	White Non-Hispanic	2010	247.0	0.090712
CLRD	Asian and Pacific Islander	2010	18.0	0.017460
CLRD	Hispanic	2010	150.0	0.064210
CLRD	Other Race/ Ethnicity	2010	0.0	0.000000
Cancer	Asian and Pacific Islander	2010	940.0	0.911812
Cancer	Black Non-Hispanic	2010	3308.0	1.777257
Cancer	Hispanic	2010	2102.0	0.899799
Cancer	Other Race/ Ethnicity	2010	59.0	0.783866
Cancer	White Non-Hispanic	2010	6846.0	2.514227
Diabetes	Asian and Pacific Islander	2010	115.0	0.111551
Diabetes	Black Non-Hispanic	2010	663.0	0.356204
Diabetes	Hispanic	2010	406.0	0.173796
Diabetes	Other Race/ Ethnicity	2010	12.0	0.159430

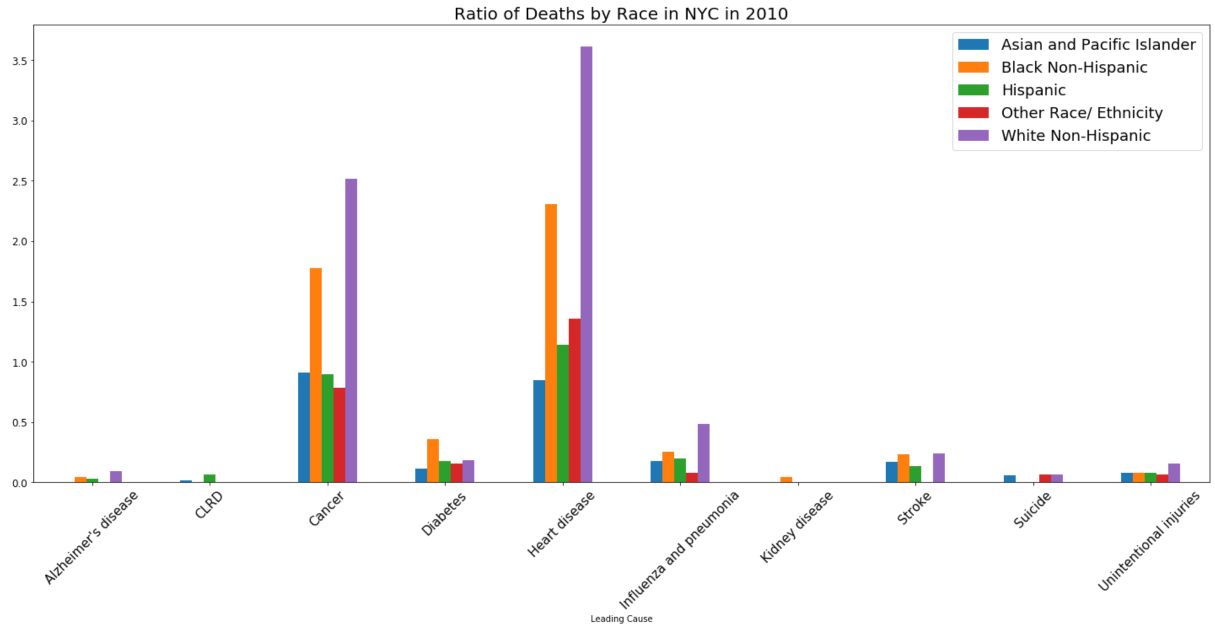
Leading Cause	Race Ethnicity	Year	Deaths	ratio
Diabetes	White Non-Hispanic	2010	503.0	0.184729
Heart disease	Asian and Pacific Islander	2010	872.0	0.845851
Heart disease	Black Non-Hispanic	2010	4297.0	2.308608
Heart disease	Hispanic	2010	2670.0	1.142942
Heart disease	Other Race/ Ethnicity	2010	102.0	1.355158
Heart disease	White Non-Hispanic	2010	9846.0	3.615992
Influenza and pneumonia	Asian and Pacific Islander	2010	182.0	0.176542
Influenza and pneumonia	Black Non-Hispanic	2010	476.0	0.255736
Influenza and pneumonia	Hispanic	2010	463.0	0.198196
Influenza and pneumonia	Other Race/ Ethnicity	2010	6.0	0.079715
Influenza and pneumonia	White Non-Hispanic	2010	1321.0	0.485144
Kidney disease	Black Non-Hispanic	2010	86.0	0.046204
Stroke	Asian and Pacific Islander	2010	172.0	0.166842
Stroke	Black Non-Hispanic	2010	430.0	0.231022
Stroke	Hispanic	2010	308.0	0.131845
Stroke	Other Race/ Ethnicity	2010	0.0	0.000000
Stroke	White Non-Hispanic	2010	658.0	0.241654
Suicide	Asian and Pacific Islander	2010	63.0	0.061111
Suicide	Other Race/ Ethnicity	2010	5.0	0.066429
Suicide	White Non-Hispanic	2010	182.0	0.066840
Unintentional injuries	Asian and Pacific Islander	2010	79.0	0.076631
Unintentional injuries	Black Non-Hispanic	2010	147.0	0.078977
Unintentional injuries	Hispanic	2010	190.0	0.081333
Unintentional injuries	Other Race/ Ethnicity	2010	5.0	0.066429

Leading Cause	Race Ethnicity	Year	Deaths	ratio
Unintentional injuries	Other Race/ Ethnicity	2010	5.0	0.066429

	Race Ethnicity	Year	Deaths	ratio
Leading Cause				
Unintentional injuries	White Non-Hispanic	2010	434.0	0.159389

In [145]:
```
#plot
fig,ax = plt.subplots()
nyc_race_2010.pivot_table(values='ratio',index='Leading Cause',columns=
'Race Ethnicity').plot.bar(ax=ax, figsize=(25,10))
ax.set_title("Ratio of Deaths by Race in NYC in 2010", size = 20)
ax.tick_params(axis='y', which='major', labelsize=12)
ax.tick_params(axis='x', which='major', labelsize=15, rotation=45)
ax.legend(prop=dict(size=18))
```

Out[145]:
```
<matplotlib.legend.Legend at 0x1a26635e90>
```



4. US vs NYC Death to Population Ratio Comparison

In [146]:
```
city = nyc.dropna().groupby(['Leading Cause','Year'],as_index=False)['D
eaths'].sum()
city = city.loc[city['Year']>2007]

ratio=[]
for index, row in city.iterrows():
    q = quotient.get(row['Year'])
    ratio.append(row['Deaths']/q)

city['ratio'] = ratio

city
```

Out[146]:

	Leading Cause	Year	Deaths	ratio
1	Alzheimer's disease	2008	151.0	0.018715
2	Alzheimer's disease	2009	354.0	0.043534
3	Alzheimer's disease	2010	406.0	0.049663
4	Alzheimer's disease	2011	435.0	0.052581
5	Alzheimer's disease	2012	463.0	0.055462
...	...	...	...	...
75	Unintentional injuries	2010	865.0	0.105809
76	Unintentional injuries	2011	750.0	0.090657
77	Unintentional injuries	2012	972.0	0.116435
78	Unintentional injuries	2013	948.0	0.112874
79	Unintentional injuries	2014	943.0	0.111764

70 rows × 4 columns

In [147]:
```
# all deaths in the us by year and cuase
country = us.loc[~(us['Cause Name']=='All causes')].groupby(['Cause Nam
e','Year'])[['Deaths']].sum()
```

```
# map years to population
us_pop = {
    #2007: nyc_pop_00_10["POPESTIMATE2007"][idx],
    2008: us_pop_00_10["TOT_POP"][98],
    2009: us_pop_00_10["TOT_POP"][110],
    2010: us_pop_10_19["CENSUS2010POP"][0],
    2011: us_pop_10_19["POPESTIMATE2011"][0],
    2012: us_pop_10_19["POPESTIMATE2012"][0],
    2013: us_pop_10_19["POPESTIMATE2013"][0],
    2014: us_pop_10_19["POPESTIMATE2014"][0]
}

# caluculate deaths to population ratio
ratio = [];
for index, row in country.reset_index().iterrows():
    q = us_pop.get(row['Year'])
    ratio.append(row['Deaths']/q)
country['ratio'] = ratio

country
```

Out[147]:

		Deaths	ratio
Cause Name	**Year**		
Alzheimer's disease	2008	164870.0	0.000543
	2009	158006.0	0.000515
	2010	166988.0	0.000541
	2011	169948.0	0.000545
	2012	167274.0	0.000533
...	...	...	...
Unintentional injuries	2010	241718.0	0.000783
	2011	252876.0	0.000812
	2012	255584.0	0.000814

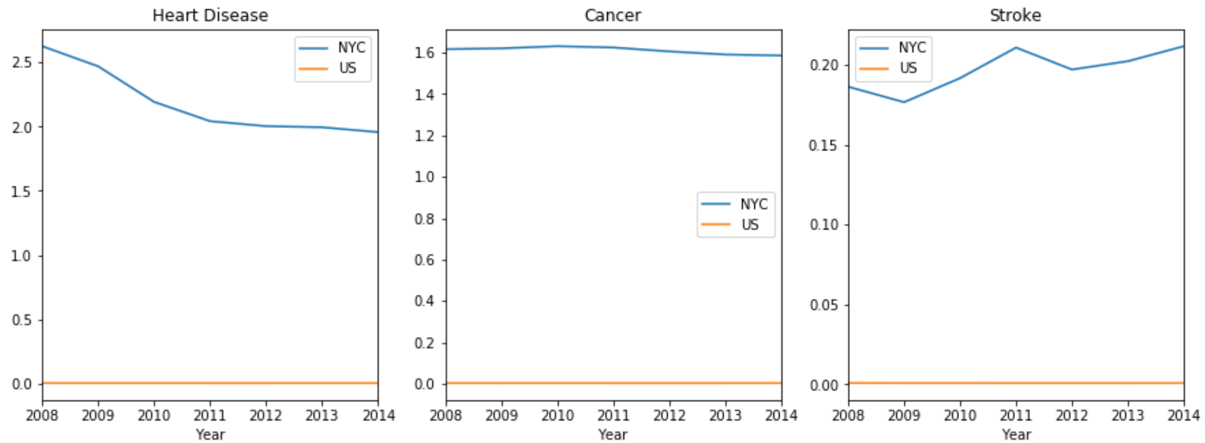
		Deaths	ratio
Cause Name	Year		
	2013	261114.0	0.000826
	2014	271856.0	0.000854

70 rows × 2 columns

In [148]:

```
fig,ax = plt.subplots(nrows=1, ncols=3, figsize=(15,5))
fig.subplots_adjust(hspace=0.5, wspace=0.2)
city_pt = city.pivot_table(values='ratio',index='Year',columns='Leading
 Cause')
country_pt = country.pivot_table(values='ratio',index='Year',columns='C
ause Name')
city_pt.plot(y='Heart disease', ax=ax[0], title='Heart Disease')
country_pt.plot(y='Heart disease', ax=ax[0], title='Heart Disease')
ax[0].legend(["NYC","US"])
city_pt.plot(y='Cancer', ax=ax[1], title='Cancer')
country_pt.plot(y='Cancer', ax=ax[1], title='Cancer')
ax[1].legend(["NYC","US"])
city_pt.plot(y='Stroke', ax=ax[2], title='Stroke')
country_pt.plot(y='Stroke', ax=ax[2], title='Stroke')
ax[2].legend(["NYC","US"])
```

Out[148]: <matplotlib.legend.Legend at 0x1a2e0f1e50>



Note that while the US data appears to remain constant, it is not, the scale is just very close to zero.

5. US Demographics Dataset

data source: https://www.census.gov/data/tables/time-series/demo/popest/2010s-state-detail.html

In [149]:

```
states = pd.read_csv('us_demographics.csv')
states.columns = states.iloc[0]
states = states.drop(columns=['Id'])[1:].loc[states['Year'].str.contain
s('July')]
states['Year'] = states['Year'].str[-4:].astype(int)
states
```

Out[149]:

	Year	Sex	Hispanic Origin	Id2	Geography	Total	Race Alone - White	Race Alone - Black or African American	Race Alone - American Indian and Alaska Native	Al
19	2010	Female	Hispanic	NaN	United States	25000565	22059599	1199204	705953	25
20	2010	Female	Not Hispanic	NaN	United States	132248502	100322803	19897522	1150332	774
21	2010	Female	Total	NaN	United States	157249067	122382402	21096726	1856285	79
22	2010	Male	Hispanic	NaN	United States	25746906	22790195	1143433	777621	25
23	2010	Male	Not Hispanic	NaN	United States	126330112	97063824	18116412	1118365	70

	Year	Sex	Hispanic Origin	Id2	Geography	Total	Race Alone - White	Race Alone - Black or African American	Race Alone - American Indian and Alaska Native	A
...	...	...	...	...	...	...	...	...	...	
5144	2018	Male	Not Hispanic	56	Wyoming	263944	245867	3985	6079	
5145	2018	Male	Total	56	Wyoming	294534	272499	4492	8004	
5146	2018	Both Sexes	Hispanic	56	Wyoming	58227	50690	959	3598	
5147	2018	Both Sexes	Not Hispanic	56	Wyoming	519510	484253	6598	12262	
5148	2018	Both Sexes	Total	56	Wyoming	577737	534943	7557	15860	

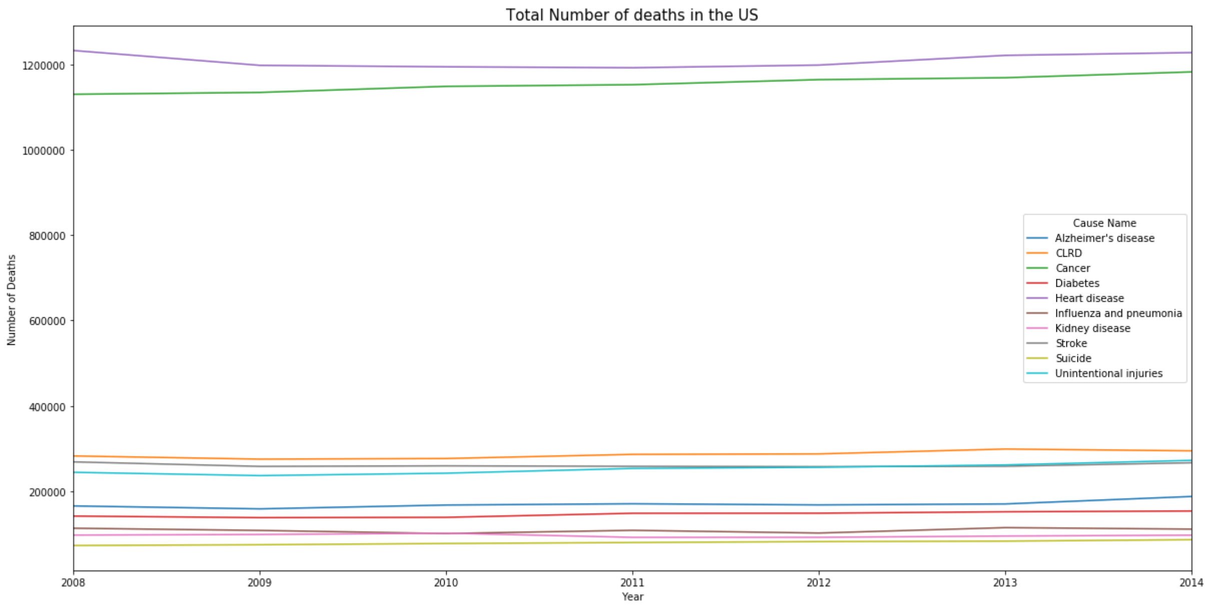
4212 rows × 12 columns

In [150]:

```
# plot us data
fig,ax = plt.subplots()
total_deaths = country.pivot_table(values='Deaths',index='Year',columns
='Cause Name')
total_deaths.plot(ax=ax, figsize=(20,10))
ax.set_ylabel('Number of Deaths')
ax.set_title('Total Number of deaths in the US', size=15)
```

Out[150]:

```
Text(0.5, 1.0, 'Total Number of deaths in the US')
```



In [151]:

```
gb_states = states.groupby(['Year','Geography','Hispanic Origin'])['Total','Race Alone - White','Race Alone - Black or African American','Race Alone - American Indian and Alaska Native','Race Alone - Asian','Race Alone - Native Hawaiian and Other Pacific Islander','Two or More Races'].sum()
gb_states = gb_states.reset_index(['Hispanic Origin'])
gb_states
```

Out[151]:

		Hispanic Origin	Total	Race Alone - White	Race Alone - Black c African America
Year	Geography				
2010	Alabama	Hispanic	82417103789186206	6874486936155680	608768621294
	Alabama	Not Hispanic	238003422192084599242	163974115701043209845	667201581121124832
	Alabama	Total	246245123229974785448	170848516570403365525	673288587983126127

Year	Geography	Hispanic Origin	Total	Race Alone - White	Race Alone - Black c African America
	Alaska	Hispanic	194602055940019	136381435627994	11751144231
	Alaska	Not Hispanic	322858351029673887	215621242341457962	9850124622231
...	...	...	...	...	.
	Wisconsin	Not Hispanic	272539926842145409613	237112323417714712894	18860918230037090
	Wisconsin	Total	292129528922735813568	254084525226815063526	19756119148638904
2018	Wyoming	Hispanic	276373059058227	240582663250690	45250795
	Wyoming	Not Hispanic	255566263944519510	238386245867484253	26133985659
	Wyoming	Total	283203294534577737	262444272499534943	30654492755

1404 rows × 8 columns

In [152]:

```
state_pop = gb_states.loc[gb_states['Hispanic Origin']=='Total']['Tota
l'].astype(float)
state_pop = state_pop.reset_index().rename(columns={'Total':'Total_pop'
})
ratio = us.loc[us['Year']>2009].merge(state_pop.loc[state_pop['Year']<2
015], left_on=['State','Year'], right_on=['Geography','Year'], how='inn
er')
ratio['Death_ratio'] = ratio['Deaths']/ratio['Total_pop']
ratio
```

Out[152]:

Year	Cause Name	State	Deaths	Age-adjusted Death Rate	Geography	Total_pop	Death_ratio

Rate

	Year	Cause Name	State	Deaths	Age-adjusted Death Rate	Geography	Total_pop	Death_ratio
0	2014	Unintentional injuries	Alabama	2463.0	49.3	Alabama	2.495006e+20	9.871719e-18
1	2014	All causes	Alabama	50215.0	909.1	Alabama	2.495006e+20	2.012620e-16
2	2014	Alzheimer's disease	Alabama	1885.0	35.3	Alabama	2.495006e+20	7.555091e-18
3	2014	Stroke	Alabama	2663.0	48.3	Alabama	2.495006e+20	1.067332e-17
4	2014	CLRD	Alabama	3050.0	53.6	Alabama	2.495006e+20	1.222442e-17
...	...	...	...	...	...	...	...	...
2855	2010	Heart disease	Wyoming	962.0	169.8	Wyoming	2.766993e+17	3.476699e-15
2856	2010	Influenza and pneumonia	Wyoming	109.0	19.5	Wyoming	2.766993e+17	3.939295e-16
2857	2010	Suicide	Wyoming	131.0	22.4	Wyoming	2.766993e+17	4.734382e-16
2858	2010	Cancer	Wyoming	1016.0	172.6	Wyoming	2.766993e+17	3.671856e-15
2859	2010	Kidney disease	Wyoming	69.0	12.5	Wyoming	2.766993e+17	2.493682e-16

2860 rows × 8 columns

In [153]:

```
#ratio of white only population to overall population in each state
white_ratio = gb_states.loc[(gb_states['Hispanic Origin']=='Not Hispani
c')]['Race Alone - White'].astype(float)/gb_states.loc[(gb_states['Hisp
anic Origin']=='Total')]['Total'].astype(float)
```

```python
white_ratio = white_ratio.reset_index()

#add ratio to us death rate dataset
ratio = ratio.merge(white_ratio.loc[white_ratio['Year']<2015], on=['Geo
graphy','Year'], how='inner')
ratio = ratio.rename(columns={0 :'white_ratio'})
ratio = ratio.set_index('Cause Name').drop(index='All causes').reset_in
dex()
ratio
```

Out[153]:

	Cause Name	Year	State	Deaths	Age-adjusted Death Rate	Geography	Total_pop	Death_ratio	whi
0	Unintentional injuries	2014	Alabama	2463.0	49.3	Alabama	2.495006e+20	9.871719e-18	0
1	Alzheimer's disease	2014	Alabama	1885.0	35.3	Alabama	2.495006e+20	7.555091e-18	0
2	Stroke	2014	Alabama	2663.0	48.3	Alabama	2.495006e+20	1.067332e-17	0
3	CLRD	2014	Alabama	3050.0	53.6	Alabama	2.495006e+20	1.222442e-17	0
4	Diabetes	2014	Alabama	1281.0	22.8	Alabama	2.495006e+20	5.134256e-18	0
...	...	...	...	...	...	...	...	...	
2595	Heart disease	2010	Wyoming	962.0	169.8	Wyoming	2.766993e+17	3.476699e-15	0
2596	Influenza and pneumonia	2010	Wyoming	109.0	19.5	Wyoming	2.766993e+17	3.939295e-16	0
2597	Suicide	2010	Wyoming	131.0	22.4	Wyoming	2.766993e+17	4.734382e-16	0
2598	Cancer	2010	Wyoming	1016.0	172.6	Wyoming	2.766993e+17	3.671856e-15	0

	Cause Name	Year	State	Deaths	Age-adjusted Death Rate	Geography	Total_pop	Death_ratio	whi
2599	Kidney disease	2010	Wyoming	69.0	12.5	Wyoming	2.766993e+17	2.493682e-16	0

2600 rows × 9 columns

In [154]:
```
# ratio of hispanic only population to overall population in each state
his_ratio = gb_states.loc[(gb_states['Hispanic Origin']=='Hispanic')][
'Total'].astype(float)/gb_states.loc[(gb_states['Hispanic Origin']=='To
tal')]['Total'].astype(float)
his_ratio = his_ratio.reset_index().rename(columns={'Total':'his_ratio'
})
ratio = ratio.merge(his_ratio.loc[his_ratio['Year']<2015], on=['Geograp
hy','Year'], how='inner')
```

In [155]:
```
#ratio of Black or African American population to overall population in
 each state
black_ratio = (gb_states.loc[(gb_states['Hispanic Origin']=='Not Hispan
ic')]['Race Alone - Black or African American'].astype(float)/gb_states
.loc[(gb_states['Hispanic Origin']=='Total')]['Total'].astype(float)).r
eset_index()
black_ratio = black_ratio.rename(columns={0 :'black_ratio'})
ratio = ratio.merge(black_ratio.loc[black_ratio['Year']<2015], on=['Geo
graphy','Year'], how='inner')

#ratio of Asian and pacific islander population to overall population i
n each state
asian_ratio = (gb_states.loc[gb_states['Hispanic Origin']=='Not Hispani
c']['Race Alone - Asian'].astype(float)/gb_states.loc[(gb_states['Hispa
nic Origin']=='Total')]['Total'].astype(float)).reset_index()
asian_ratio = asian_ratio.rename(columns={0 :'asian_ratio'})
ratio = ratio.merge(asian_ratio.loc[asian_ratio['Year']<2015], on=['Geo
graphy','Year'], how='inner')
```

```python
#without United States
ratio = ratio.loc[~(ratio['Geography']=='United States')]
ratio
```

Out[155]:

	Cause Name	Year	State	Deaths	Age-adjusted Death Rate	Geography	Total_pop	Death_ratio	whi
0	Unintentional injuries	2014	Alabama	2463.0	49.3	Alabama	2.495006e+20	9.871719e-18	0
1	Alzheimer's disease	2014	Alabama	1885.0	35.3	Alabama	2.495006e+20	7.555091e-18	0
2	Stroke	2014	Alabama	2663.0	48.3	Alabama	2.495006e+20	1.067332e-17	0
3	CLRD	2014	Alabama	3050.0	53.6	Alabama	2.495006e+20	1.222442e-17	0
4	Diabetes	2014	Alabama	1281.0	22.8	Alabama	2.495006e+20	5.134256e-18	0
...	...	...	...	...	...	...	...	...	
2595	Heart disease	2010	Wyoming	962.0	169.8	Wyoming	2.766993e+17	3.476699e-15	0
2596	Influenza and pneumonia	2010	Wyoming	109.0	19.5	Wyoming	2.766993e+17	3.939295e-16	0
2597	Suicide	2010	Wyoming	131.0	22.4	Wyoming	2.766993e+17	4.734382e-16	0
2598	Cancer	2010	Wyoming	1016.0	172.6	Wyoming	2.766993e+17	3.671856e-15	0
2599	Kidney disease	2010	Wyoming	69.0	12.5	Wyoming	2.766993e+17	2.493682e-16	0

2550 rows × 12 columns

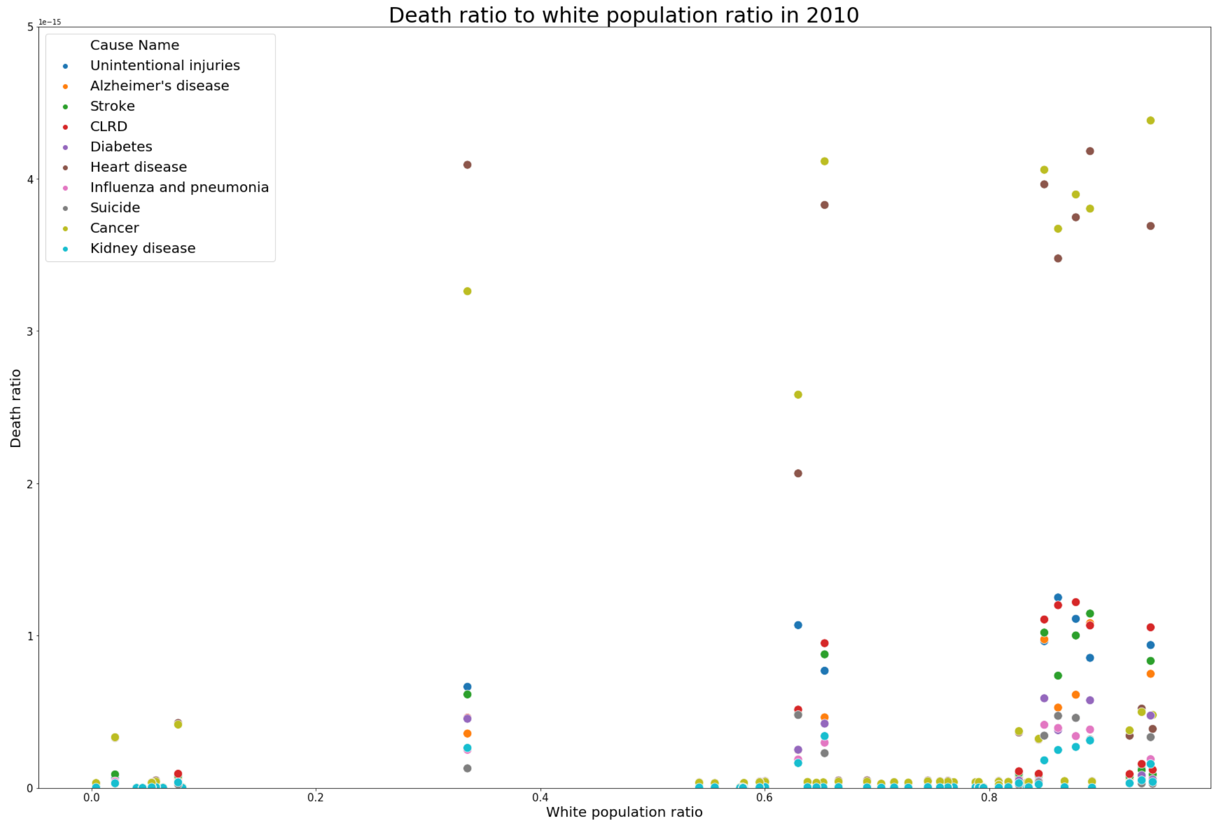
In [156]:
```python
ratio_2010 = ratio.loc[ratio['Year']==2010]
```

```
print(ratio_2010['Death_ratio'].min(),ratio_2010['Death_ratio'].max())
```

```
1.657586146147e-20 4.382618897551117e-15
```

In [157]:

```
#plot
figure, ax = plt.subplots(figsize=(30,20))
sb.scatterplot(x='white_ratio',y='Death_ratio',data=ratio_2010, hue='Ca
use Name', s=150, ax=ax)

ax.tick_params(labelsize=15)
ax.set_xlabel('White population ratio',size=20)
ax.set_ylabel('Death ratio',size=20)
ax.set_title("Death ratio to white population ratio in 2010", size = 30
)
ax.legend(prop={'size':20})

#set y limits based on max and min
ax.set_ylim(0,5e-15)

plt.show()
```



In [158]:

```
reg = smf.ols("Death_ratio ~ white_ratio + black_ratio + his_ratio + as
ian_ratio", data = ratio).fit()
print(reg.summary())
```

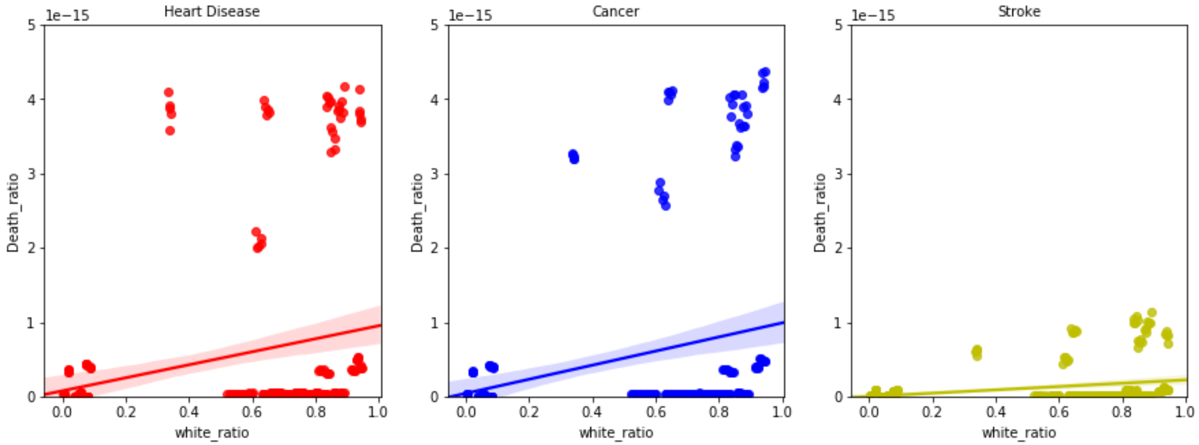
```
                            OLS Regression Results

==============================================================================
=======
Dep. Variable:            Death_ratio   R-squared:
  0.047
Model:                            OLS   Adj. R-squared:
  0.045
Method:                 Least Squares   F-statistic:
```

```
  31.17
Date:                Wed, 13 May 2020   Prob (F-statistic):
2.22e-25
Time:                        20:05:08   Log-Likelihood:
85663.
No. Observations:                2550   AIC:                            -1.
713e+05
Df Residuals:                    2545   BIC:                            -1.
713e+05
Df Model:                           4

Covariance Type:            nonrobust

=======================================================================
========
                  coef    std err          t      P>|t|      [0.025
  0.975]
-----------------------------------------------------------------------
--------
Intercept   -4.765e-17    3.1e-17     -1.536      0.125   -1.08e-16
1.32e-17
white_ratio  3.716e-16   4.41e-17      8.435      0.000    2.85e-16
4.58e-16
black_ratio  1.208e-15   1.58e-16      7.642      0.000    8.98e-16
1.52e-15
his_ratio    -8.36e-16   4.51e-16     -1.856      0.064   -1.72e-15
4.74e-17
asian_ratio  3.484e-15   2.34e-15      1.490      0.136    -1.1e-15
8.07e-15
=======================================================================
=======
Omnibus:                     2413.540   Durbin-Watson:
  1.751
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             69
766.203
Skew:                           4.735   Prob(JB):
   0.00
Kurtosis:                      26.811   Cond. No.
   223.
```

```
==============================================================================
=======

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

In [159]:
```
heart_d = ratio.loc[ratio['Cause Name']=='Heart disease']
cancer = ratio.loc[ratio['Cause Name']=='Cancer']
stroke = ratio.loc[ratio['Cause Name']=='Stroke']


#plot
fig,ax = plt.subplots(nrows=1, ncols=3,figsize=(15,5))

sb.regplot(x="white_ratio", y="Death_ratio", data=heart_d, ax=ax[0],color='r')

sb.regplot(x="white_ratio", y="Death_ratio", data=cancer, ax=ax[1],color='b')

sb.regplot(x="white_ratio", y="Death_ratio", data=stroke, ax=ax[2],color='y')

ax[0].set_title("Heart Disease", size = 10)
ax[1].set_title("Cancer", size = 10)
ax[2].set_title("Stroke", size = 10)

#set y limits based on max and min
ax[0].set_ylim(0,5e-15)
ax[1].set_ylim(0,5e-15)
ax[2].set_ylim(0,5e-15)
```

Out[159]:
```
(0, 5e-15)
```



Based on the regression and plots, we can see that population ratio of race does not have a lot of explanatory power in the cause of deaths in the US. R squared is only 0.047 and the p values for his_ratio and asian_ratio shows that they are not significant. From the scatter plots, we can see that for heart disease, cancer, and stroke, the regression line does not really go through the points and they have a pretty similar pattern. This may be a result of same states following the same pattern for different causes of death.

IV. Conclusion

The goal of this project was to analyze the disparity between different causes of death in New York City and the rest of the country. What we discovered was the variables we found thought provoking and promising in terms of statistical significance did not paint the whole picture. If we had more time and resources, we could have investigated further into other variables that may provide a deeper explanation to the effects that we visualized. Overall, our analysis has brought us a deeper understanding of the causes of death in New York City and the rest of the country, the variables that do and do not effect them, and an idea of how further research can benefit society. Results from further research could potentially help local and federal government agencies, as well as private businesses, do a better job to create a more healthy and prepared country.

In [ ]:

In [ ]:

In [ ]: