Project: FBI Gun Data Analysis

Table of Contents

Introduction

In this project we will investigate two sets of data.

The first set comes from the FBI's National Instant Criminal Background Check System. It includes records of requested background checks by Gun shops to check if the customer has any criminal records.

The second data set has been supplemented with state level data from census.gov.

We will try and answer a couple of questions by exploring those two data sets like:

- Did gun registerations grow over the years
- Is there a certain type of gun that was more popular
- Which states has the most gun regesterations
- Which states have the highest gun registeration per capita ?

In [ ]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

Data Wrangling

General Properties

In [ ]:

```
# Loading up the data
df=pd.read_csv('u.s.-census-data.csv')
df_gun=pd.read_excel('gun-data.xlsx')
```

In [ ]:

```
# Displaying the first set to check it
df.head()
```

Out[ ]:

	Fact	Fact Note	Alabama	Alaska	Arizona	Arkansas	California	Colorado	Connecticut	Delaware	...	South Dakota	Tennessee	Texas	Utah	Vermont	Virginia	Washington	West Virginia	Wisconsin	Wyoming
0	Population estimates, July 1, 2016, (V2016)	NaN	4,863,300	741,894	6,931,071	2,988,248	39,250,017	5,540,545	3,576,452	952,065	...	865454	6651194	27,862,596	3,051,217	624,594	8,411,808	7,288,000	1,831,102	5,778,708	585,501
1	Population estimates base, April 1, 2010, (V2...	NaN	4,780,131	710,249	6,392,301	2,916,025	37,254,522	5,029,324	3,574,114	897,936	...	814195	6346298	25,146,100	2,763,888	625,741	8,001,041	6,724,545	1,853,011	5,687,289	563,767
2	Population, percent change - April 1, 2010 (es...	NaN	1.70%	4.50%	8.40%	2.50%	5.40%	10.20%	0.10%	6.00%	...	0.063	0.048	10.80%	10.40%	-0.20%	5.10%	8.40%	-1.20%	1.60%	3.90%
3	Population, Census, April 1, 2010	NaN	4,779,736	710,231	6,392,017	2,915,918	37,253,956	5,029,196	3,574,097	897,934	...	814180	6346105	25,145,561	2,763,885	625,741	8,001,024	6,724,540	1,852,994	5,686,986	563,626
4	Persons under 5 years, percent, July 1, 2016, ...	NaN	6.00%	7.30%	6.30%	6.40%	6.30%	6.10%	5.20%	5.80%	...	0.071	0.061	7.20%	8.30%	4.90%	6.10%	6.20%	5.50%	5.80%	6.50%

5 rows × 52 columns

In [ ]:

```
# Checking if there are missing data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 85 entries, 0 to 84
Data columns (total 52 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Fact            80 non-null     object
 1   Fact Note       28 non-null     object
 2   Alabama         65 non-null     object
 3   Alaska          65 non-null     object
 4   Arizona         65 non-null     object
 5   Arkansas        65 non-null     object
 6   California      65 non-null     object
 7   Colorado        65 non-null     object
 8   Connecticut     65 non-null     object
 9   Delaware        65 non-null     object
 10  Florida         65 non-null     object
 11  Georgia         65 non-null     object
 12  Hawaii          65 non-null     object
 13  Idaho           65 non-null     object
 14  Illinois        65 non-null     object
 15  Indiana         65 non-null     object
 16  Iowa            65 non-null     object
 17  Kansas          65 non-null     object
 18  Kentucky        65 non-null     object
 19  Louisiana       65 non-null     object
 20  Maine           65 non-null     object
 21  Maryland        65 non-null     object
 22  Massachusetts   65 non-null     object
 23  Michigan        65 non-null     object
 24  Minnesota       65 non-null     object
 25  Mississippi     65 non-null     object
 26  Missouri        65 non-null     object
 27  Montana         65 non-null     object
 28  Nebraska        65 non-null     object
 29  Nevada          65 non-null     object
 30  New Hampshire   65 non-null     object
 31  New Jersey      65 non-null     object
 32  New Mexico      65 non-null     object
 33  New York        65 non-null     object
 34  North Carolina  65 non-null     object
 35  North Dakota    65 non-null     object
 36  Ohio            65 non-null     object
 37  Oklahoma        65 non-null     object
 38  Oregon          65 non-null     object
 39  Pennsylvania    65 non-null     object
 40  Rhode Island    65 non-null     object
 41  South Carolina  65 non-null     object
 42  South Dakota    65 non-null     object
 43  Tennessee       65 non-null     object
 44  Texas           65 non-null     object
 45  Utah            65 non-null     object
 46  Vermont         65 non-null     object
 47  Virginia        65 non-null     object
 48  Washington      65 non-null     object
 49  West Virginia   65 non-null     object
 50  Wisconsin       65 non-null     object
 51  Wyoming         65 non-null     object
dtypes: object(52)
memory usage: 34.7+ KB
```

- It seems that the census data is not missing data aside from the fact note which can be discarded
- Also it would be better to transpose the data to be able to compare/merge them later with the second dataframe

In [ ]:
```python
# Checking the data types in case any needs to be changed
df.dtypes
```

Out[ ]:
```
Fact              object
Fact Note         object
Alabama           object
Alaska            object
Arizona           object
Arkansas          object
California        object
Colorado          object
Connecticut       object
Delaware          object
Florida           object
Georgia           object
Hawaii            object
Idaho             object
Illinois          object
Indiana           object
Iowa              object
Kansas            object
Kentucky          object
Louisiana         object
Maine             object
Maryland          object
Massachusetts     object
Michigan          object
Minnesota         object
Mississippi       object
Missouri          object
Montana           object
Nebraska          object
Nevada            object
New Hampshire     object
New Jersey        object
New Mexico        object
New York          object
North Carolina    object
North Dakota      object
Ohio              object
Oklahoma          object
Oregon            object
Pennsylvania      object
Rhode Island      object
South Carolina    object
South Dakota      object
Tennessee         object
Texas             object
Utah              object
Vermont           object
Virginia          object
Washington        object
West Virginia     object
Wisconsin         object
Wyoming           object
dtype: object
```

- We'll need to change the types of the data into floats to be able to display later

In [ ]:
```python
# Checking the second data set
df_gun.head()
```

Out[ ]:

	month	state	permit	permit_recheck	handgun	long_gun	other	multiple	admin	prepawn_handgun	...	returned_other	rentals_handgun	rentals_long_gun	private_sale_handgun	private_sale_long_gun	private_sale_other	return_to_sell
0	2017-09	Alabama	16717.0	0.0	5734.0	6320.0	221.0	317	0.0	15.0	...	0.0	0.0	0.0	9.0	16.0	3.0	
1	2017-09	Alaska	209.0	2.0	2320.0	2930.0	219.0	160	0.0	5.0	...	0.0	0.0	0.0	17.0	24.0	1.0	
2	2017-09	Arizona	5069.0	382.0	11063.0	7946.0	920.0	631	0.0	13.0	...	0.0	0.0	0.0	38.0	12.0	2.0	
3	2017-09	Arkansas	2935.0	632.0	4347.0	6063.0	165.0	366	51.0	12.0	...	0.0	0.0	0.0	13.0	23.0	0.0	
4	2017-09	California	57839.0	0.0	37165.0	24581.0	2984.0	0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	

5 rows × 27 columns

In [ ]:
```python
# Checking missing data
df_gun.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12485 entries, 0 to 12484
Data columns (total 27 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   month                      12485 non-null  object 
 1   state                      12485 non-null  object 
 2   permit                     12461 non-null  float64
 3   permit_recheck             1100 non-null   float64
 4   handgun                    12465 non-null  float64
 5   long_gun                   12466 non-null  float64
 6   other                      5500 non-null   float64
 7   multiple                   12485 non-null  int64  
 8   admin                      12462 non-null  float64
 9   prepawn_handgun            10542 non-null  float64
 10  prepawn_long_gun           10540 non-null  float64
 11  prepawn_other              5115 non-null   float64
 12  redemption_handgun         10545 non-null  float64
 13  redemption_long_gun        10544 non-null  float64
 14  redemption_other           5115 non-null   float64
 15  returned_handgun           2200 non-null   float64
 16  returned_long_gun          2145 non-null   float64
 17  returned_other             1815 non-null   float64
 18  rentals_handgun            990 non-null    float64
 19  rentals_long_gun           825 non-null    float64
 20  private_sale_handgun       2750 non-null   float64
 21  private_sale_long_gun      2750 non-null   float64
 22  private_sale_other         2750 non-null   float64
 23  return_to_seller_handgun   2475 non-null   float64
 24  return_to_seller_long_gun  2750 non-null   float64
 25  return_to_seller_other     2255 non-null   float64
 26  totals                     12485 non-null  int64  
dtypes: float64(23), int64(2), object(2)
memory usage: 2.6+ MB
```

- The null data does not seem to make a problem since it is not age or something that has to have a value other than zero

Data Cleaning

We will perform some data cleaning in order to better handle the data based on the previous deductions like:

- Removing the fact note column from the census data set
- Transposing the census data set to match the NICS data set
- Cleaning the census data set of non required columns

- Changing data types to ones that can be better handled
- Adding columns for years since we will check for the trend over the years

In [ ]:
```python
# Will start with removing the fact note column
df.drop(columns='Fact Note',inplace=True)
df.head()
```

Out[ ]:

	Fact	Alabama	Alaska	Arizona	Arkansas	California	Colorado	Connecticut	Delaware	Florida	...	South Dakota	Tennessee	Texas	Utah	Vermont	Virginia	Washington	West Virginia	Wisconsin	Wyoming
0	Population estimates, July 1, 2016, (V2016)	4,863,300	741,894	6,931,071	2,988,248	39,250,017	5,540,545	3,576,452	952,065	20,612,439	...	865454	6651194	27,862,596	3,051,217	624,594	8,411,808	7,288,000	1,831,102	5,778,708	585,501
1	Population estimates base, April 1, 2010, (V2...	4,780,131	710,249	6,392,301	2,916,025	37,254,522	5,029,324	3,574,114	897,936	18,804,592	...	814195	6346298	25,146,100	2,763,888	625,741	8,001,041	6,724,545	1,853,011	5,687,289	563,767
2	Population, percent change - April 1, 2010 (es...	1.70%	4.50%	8.40%	2.50%	5.40%	10.20%	0.10%	6.00%	9.60%	...	0.063	0.048	10.80%	10.40%	-0.20%	5.10%	8.40%	-1.20%	1.60%	3.90%
3	Population, Census, April 1, 2010	4,779,736	710,231	6,392,017	2,915,918	37,253,956	5,029,196	3,574,097	897,934	18,801,310	...	814180	6346105	25,145,561	2,763,885	625,741	8,001,024	6,724,540	1,852,994	5,686,986	563,626
4	Persons under 5 years, percent, July 1, 2016, ...	6.00%	7.30%	6.30%	6.40%	6.30%	6.10%	5.20%	5.80%	5.50%	...	0.071	0.061	7.20%	8.30%	4.90%	6.10%	6.20%	5.50%	5.80%	6.50%

5 rows × 51 columns

In [ ]:
```python
# After trying to transpose the data frame it kept returning the index as the column name
# so after searching i will set the index to the first column and then transpose the data frame
df.set_index('Fact',inplace=True)
```

In [ ]:
```python
# Next i'll transpose the data frame to be able to compare/merge it with the second data frame
df_trns=df.transpose()
```

In [ ]:
```python
# Dropping all the non required columns at the end
df_trns.drop(df_trns.columns[20:],axis=1,inplace=True)
```

In [ ]:
```python
# Dropping columns that are not related to 2016 since this is the year that will be studied later
cols_to_drop=[]
iter=[1,2,3,5,7,9,11]
for i in iter:
    cols_to_drop.append(df_trns.columns[i])
df_trns.drop(cols_to_drop,axis=1,inplace=True)
```

In [ ]:
```python
# Changing the data types into floats to be ablt to add them or perform any other operation
# After trying to change the  types there was some values that are numbers so we will remove them first
df_trns.replace(to_replace='Z',value=0,inplace=True)
df_trns.head()
```

Out[ ]:

Fact	Population estimates, July 1, 2016, (V2016)	Persons under 5 years, percent, July 1, 2016, (V2016)	Persons under 18 years, percent, July 1, 2016, (V2016)	Persons 65 years and over, percent, July 1, 2016, (V2016)	Female persons, percent, July 1, 2016, (V2016)	White alone, percent, July 1, 2016, (V2016)	Black or African American alone, percent, July 1, 2016, (V2016)	American Indian and Alaska Native alone, percent, July 1, 2016, (V2016)	Asian alone, percent, July 1, 2016, (V2016)	Native Hawaiian and Other Pacific Islander alone, percent, July 1, 2016, (V2016)	Two or More Races, percent, July 1, 2016, (V2016)	Hispanic or Latino, percent, July 1, 2016, (V2016)	White alone, not Hispanic or Latino, percent, July 1, 2016, (V2016)
Alabama	4,863,300	6.00%	22.60%	16.10%	51.60%	69.30%	26.80%	0.70%	1.40%	0.10%	1.60%	4.20%	65.80%
Alaska	741,894	7.30%	25.20%	10.40%	47.70%	66.10%	3.80%	15.20%	6.30%	1.30%	7.30%	7.00%	61.20%
Arizona	6,931,071	6.30%	23.50%	16.90%	50.30%	83.30%	4.90%	5.40%	3.40%	0.30%	2.80%	30.90%	55.50%
Arkansas	2,988,248	6.40%	23.60%	16.30%	50.90%	79.40%	15.70%	1.00%	1.60%	0.30%	2.00%	7.30%	72.90%
California	39,250,017	6.30%	23.20%	13.60%	50.30%	72.70%	6.50%	1.70%	14.80%	0.50%	3.80%	38.90%	37.70%

In [ ]:
```python
# Changing the data types into floats
for c in df_trns.columns:
    if df_trns[c].dtypes != 'float64':
        df_trns[c]=df_trns[c].str.replace('%|,',"").astype('float')
```

```
C:\Users\Fouad\AppData\Local\Temp/ipykernel_1404/4170818147.py:4: FutureWarning: The default value of regex will change from True to False in a future version.
  df_trns[c]=df_trns[c].str.replace('%|,',"").astype('float')
```

In [ ]:
```python
# renaming the month column a proper name since we will add a column later with the name month for the months
df_gun.rename(columns={'month':'date'},inplace=True)
df_gun.head()
```

Out[ ]:

	date	state	permit	permit_recheck	handgun	long_gun	other	multiple	admin	prepawn_handgun	...	returned_other	rentals_handgun	rentals_long_gun	private_sale_handgun	private_sale_long_gun	private_sale_other	return_to_selle
0	2017-09	Alabama	16717.0	0.0	5734.0	6320.0	221.0	317	0.0	15.0	...	0.0	0.0	0.0	9.0	16.0	3.0	
1	2017-09	Alaska	209.0	2.0	2320.0	2930.0	219.0	160	0.0	5.0	...	0.0	0.0	0.0	17.0	24.0	1.0	
2	2017-09	Arizona	5069.0	382.0	11063.0	7946.0	920.0	631	0.0	13.0	...	0.0	0.0	0.0	38.0	12.0	2.0	
3	2017-09	Arkansas	2935.0	632.0	4347.0	6063.0	165.0	366	51.0	12.0	...	0.0	0.0	0.0	13.0	23.0	0.0	
4	2017-09	California	57839.0	0.0	37165.0	24581.0	2984.0	0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	

5 rows × 27 columns

In [ ]:
```python
# Changing the date column data type to be able to extract month and year from
df_gun['date']=pd.to_datetime(df_gun['date'])
df_gun['date'].dtype
```

Out[ ]:
```
dtype('<M8[ns]')
```

In [ ]:
```python
# Adding columns for the year and month to use later
df_gun['year']=df_gun['date'].dt.year
df_gun['month']=df_gun['date'].dt.month_name()
df_gun.head()
```

Out[ ]:

	date	state	permit	permit_recheck	handgun	long_gun	other	multiple	admin	prepawn_handgun	...	rentals_long_gun	private_sale_handgun	private_sale_long_gun	private_sale_other	return_to_seller_handgun	return_to_seller_long_g
0	2017-09-01	Alabama	16717.0	0.0	5734.0	6320.0	221.0	317	0.0	15.0	...	0.0	9.0	16.0	3.0	0.0	
1	2017-09-01	Alaska	209.0	2.0	2320.0	2930.0	219.0	160	0.0	5.0	...	0.0	17.0	24.0	1.0	0.0	
2	2017-09-01	Arizona	5069.0	382.0	11063.0	7946.0	920.0	631	0.0	13.0	...	0.0	38.0	12.0	2.0	0.0	
3	2017-09-01	Arkansas	2935.0	632.0	4347.0	6063.0	165.0	366	51.0	12.0	...	0.0	13.0	23.0	0.0	0.0	
4	2017-09-01	California	57839.0	0.0	37165.0	24581.0	2984.0	0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	

5 rows × 29 columns

Exploratory Data Analysis

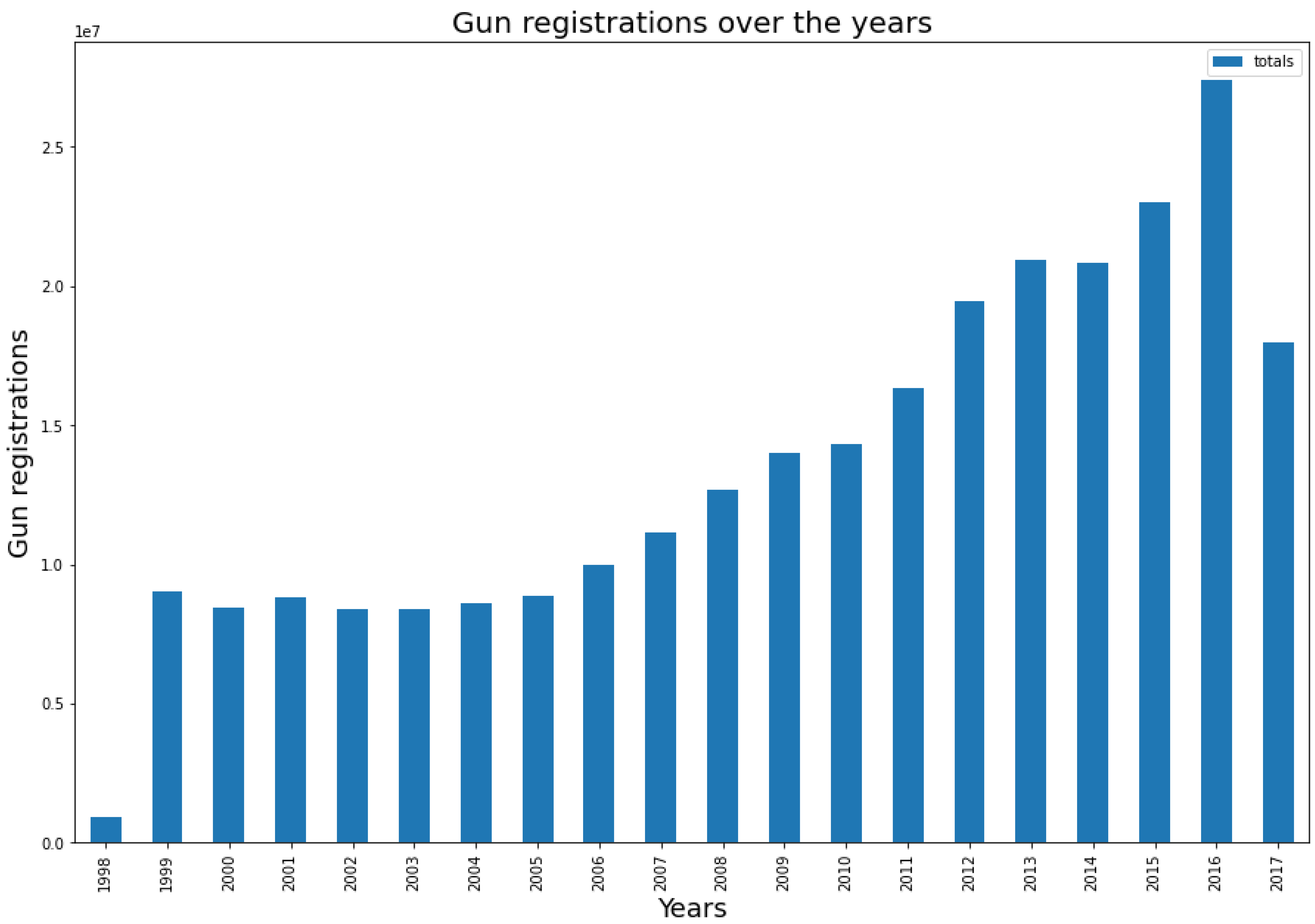
Q1 Did gun registrations grow over the years

In [ ]:
```
guns_by_year=df_gun.groupby('year').sum()
```

In [ ]:
```
# Creating a function to plot columns with different
def plott(col,type):
    guns_by_year.plot(y=col,kind=type,figsize=(15,10));
```

In [ ]:
```
# To answer that question we need to group the NICS data by year from the year column we added
# using the predefined function

plott('totals','bar')
plt.title('Gun registrations over the years', fontsize=20)
plt.xlabel('Years', fontsize=18)
plt.ylabel('Gun registrations', fontsize=18)
```

Out[ ]:
```
Text(0, 0.5, 'Gun registrations')
```

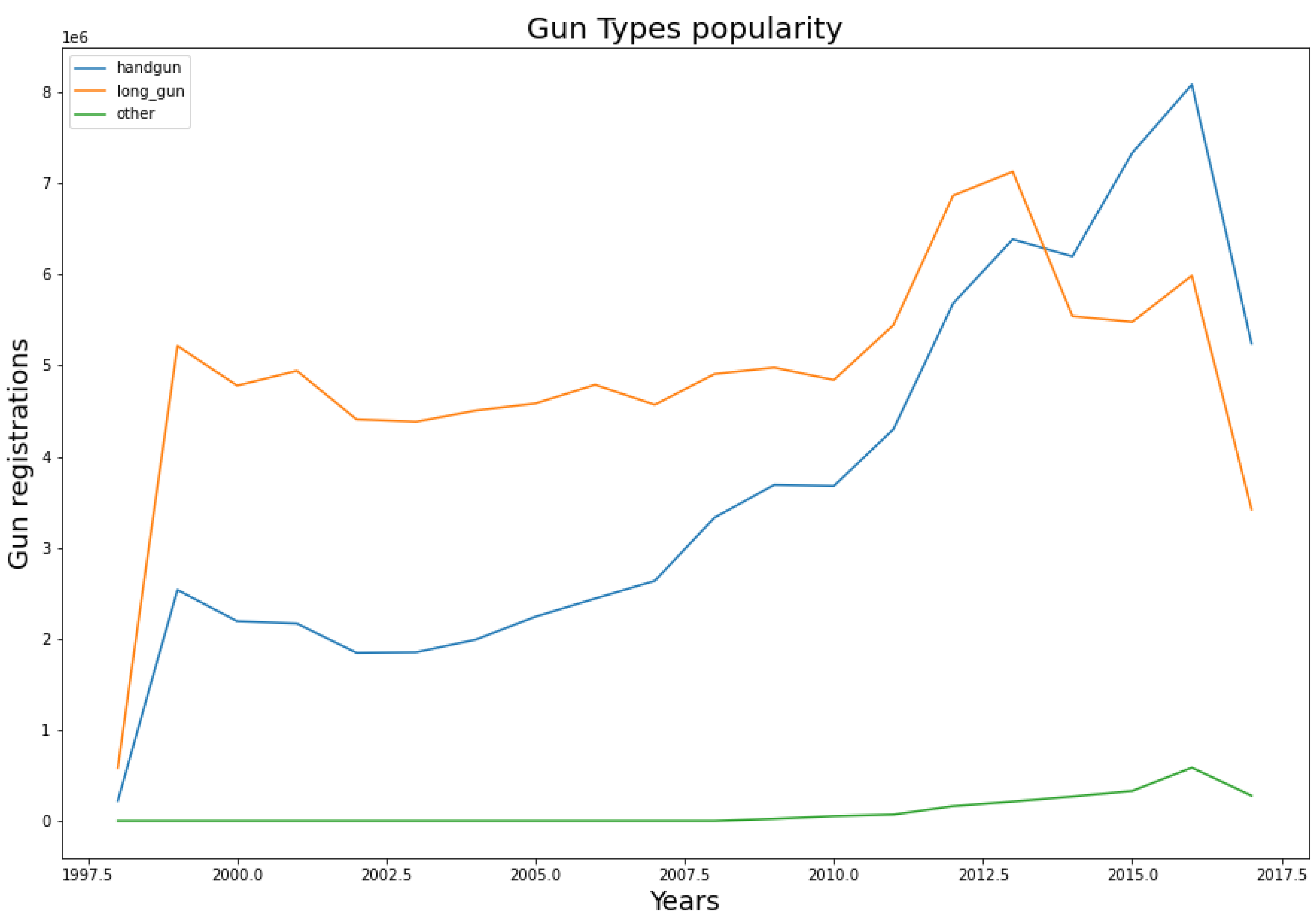


It seems the gun registeration was steady from 1999 till 2004 then it increased over the years until it reached its peak on 2016 then decreased

Q2 Is there a certain type of gun that was more popular

In [ ]:
```
# We will check the main bulk amount of guns registerations, ignoring the rentals, private sales and pawns
# So will again use the grouped data frame but will display the three types using the pre-defined function
plott(['handgun','long_gun','other'],'line')
plt.title('Gun Types popularity', fontsize=20)
plt.xlabel('Years', fontsize=18)
plt.ylabel('Gun registrations', fontsize=18)
```

Out[ ]:
```
Text(0, 0.5, 'Gun registrations')
```



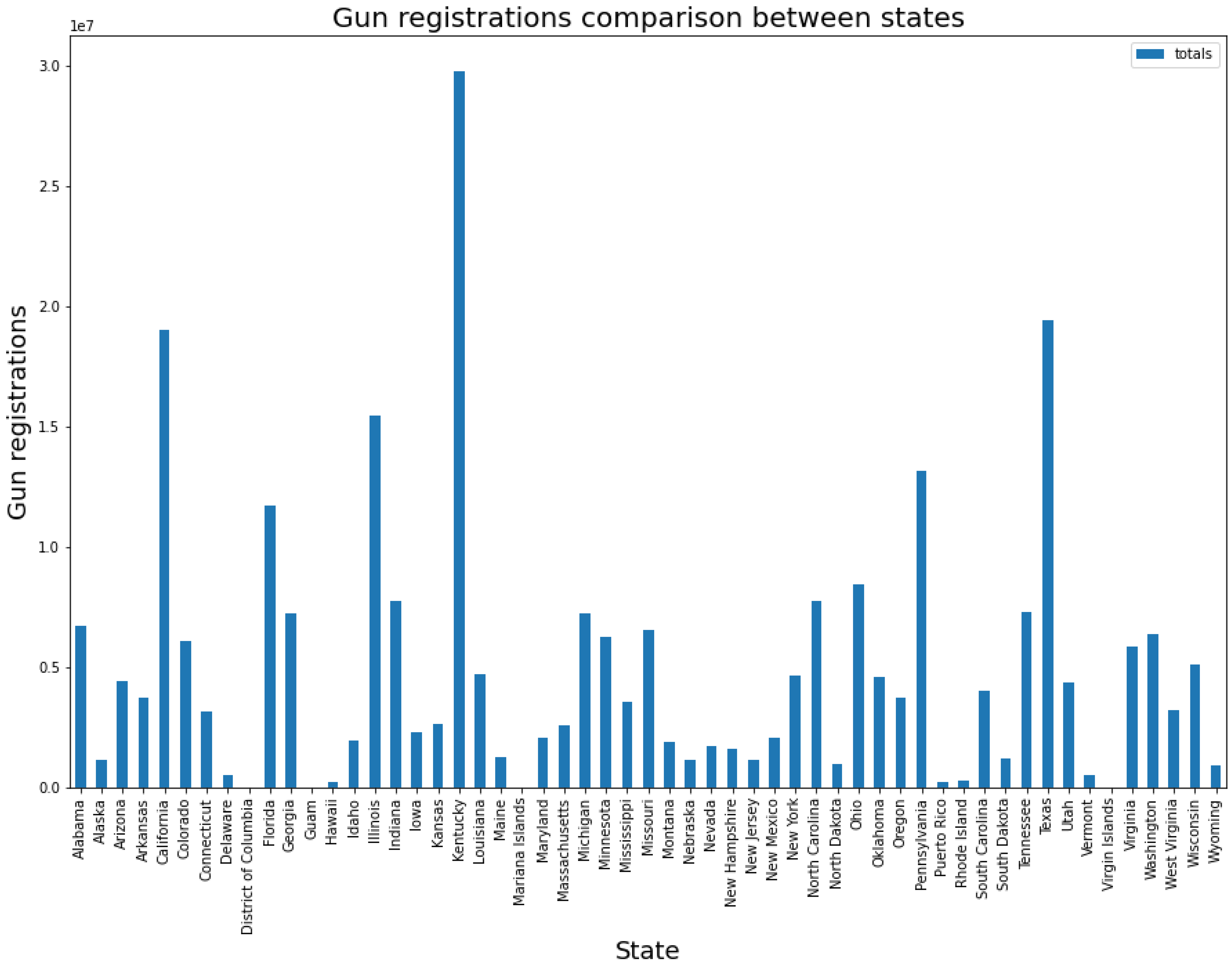
According to the above graph the long guns where more popular with the handguns closing the gap untill 2013-2014 the handguns became more popular

The other types registerations did not change for the most part with the slight rise from 2015 to 2016

Q3 Which states has the most gun regesterations

In [ ]:
```
# For that we will group the NICS data frame by state

guns_by_state=df_gun.groupby('state').sum()
guns_by_state.plot(y=['totals'],kind='bar',figsize=(15,10));
plt.title('Gun registrations comparison between states', fontsize=20)
plt.xlabel('State', fontsize=18)
plt.ylabel('Gun registrations', fontsize=18)
```

Out[ ]:
```
Text(0, 0.5, 'Gun registrations')
```



Kentucky, California and Texas seems to be the highest in gun registeration However that can be related to population

Q4 Which states have the highest gun registeration per capita ?

In [ ]:

```
# To check the gun registerations per capita we will filter the NICS data to get the 2016 gun registeration
# and compare it against the populations of the states

gun_date_2016=df_gun.query('year == 2016').groupby('state').sum()
gun_date_2016.head()
```

Out[ ]:

state	permit	permit_recheck	handgun	long_gun	other	multiple	admin	prepawn_handgun	prepawn_long_gun	prepawn_other	...	rentals_handgun	rentals_long_gun	private_sale_handgun	private_sale_long_gun	private_sale_other
Alabama	291039.0	0.0	153123.0	121963.0	6104.0	6545	5.0	111.0	114.0	2.0	...	0.0	0.0	72.0	65.0	4.0
Alaska	3121.0	0.0	37491.0	36887.0	2889.0	2316	0.0	84.0	70.0	0.0	...	0.0	0.0	39.0	66.0	1.0
Arizona	87771.0	5109.0	166784.0	108988.0	13122.0	7908	0.0	74.0	60.0	3.0	...	0.0	0.0	76.0	56.0	11.0
Arkansas	55456.0	7036.0	80244.0	82120.0	3059.0	4400	143.0	77.0	116.0	3.0	...	0.0	0.0	72.0	64.0	6.0
California	1036981.0	0.0	560355.0	554550.0	211707.0	0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0

5 rows × 26 columns

In [ ]:

```
# Next we will add the filtered NICS data to the 2016 census

combined=pd.concat([df_trns,gun_date_2016],axis=1,join='inner')
combined.head()
```

Out[ ]:

	Population estimates, July 1, 2016, (V2016)	Persons under 5 years, percent, July 1, 2016, (V2016)	Persons under 18 years, percent, July 1, 2016, (V2016)	Persons 65 years and over, percent, July 1, 2016, (V2016)	Female persons, percent, July 1, 2016, (V2016)	White alone, percent, July 1, 2016, (V2016)	Black or African American alone, percent, July 1, 2016, (V2016)	American Indian and Alaska Native alone, percent, July 1, 2016, (V2016)	Asian alone, percent, July 1, 2016, (V2016)	Native Hawaiian and Other Pacific Islander alone, percent, July 1, 2016, (V2016)	...	rentals_handgun	rentals_long_gun	private_sale_handgun	private_sale_long_gun	private_sale_other	return_to_seller_handgun	re
Alabama	4863300.0	6.0	22.6	16.1	51.6	69.3	26.8	0.7	1.4	0.1	...	0.0	0.0	72.0	65.0	4.0	3.0	
Alaska	741894.0	7.3	25.2	10.4	47.7	66.1	3.8	15.2	6.3	1.3	...	0.0	0.0	39.0	66.0	1.0	2.0	
Arizona	6931071.0	6.3	23.5	16.9	50.3	83.3	4.9	5.4	3.4	0.3	...	0.0	0.0	76.0	56.0	11.0	11.0	
Arkansas	2988248.0	6.4	23.6	16.3	50.9	79.4	15.7	1.0	1.6	0.3	...	0.0	0.0	72.0	64.0	6.0	7.0	
California	39250017.0	6.3	23.2	13.6	50.3	72.7	6.5	1.7	14.8	0.5	...	0.0	0.0	0.0	0.0	0.0	0.0	

5 rows × 39 columns

In [ ]:

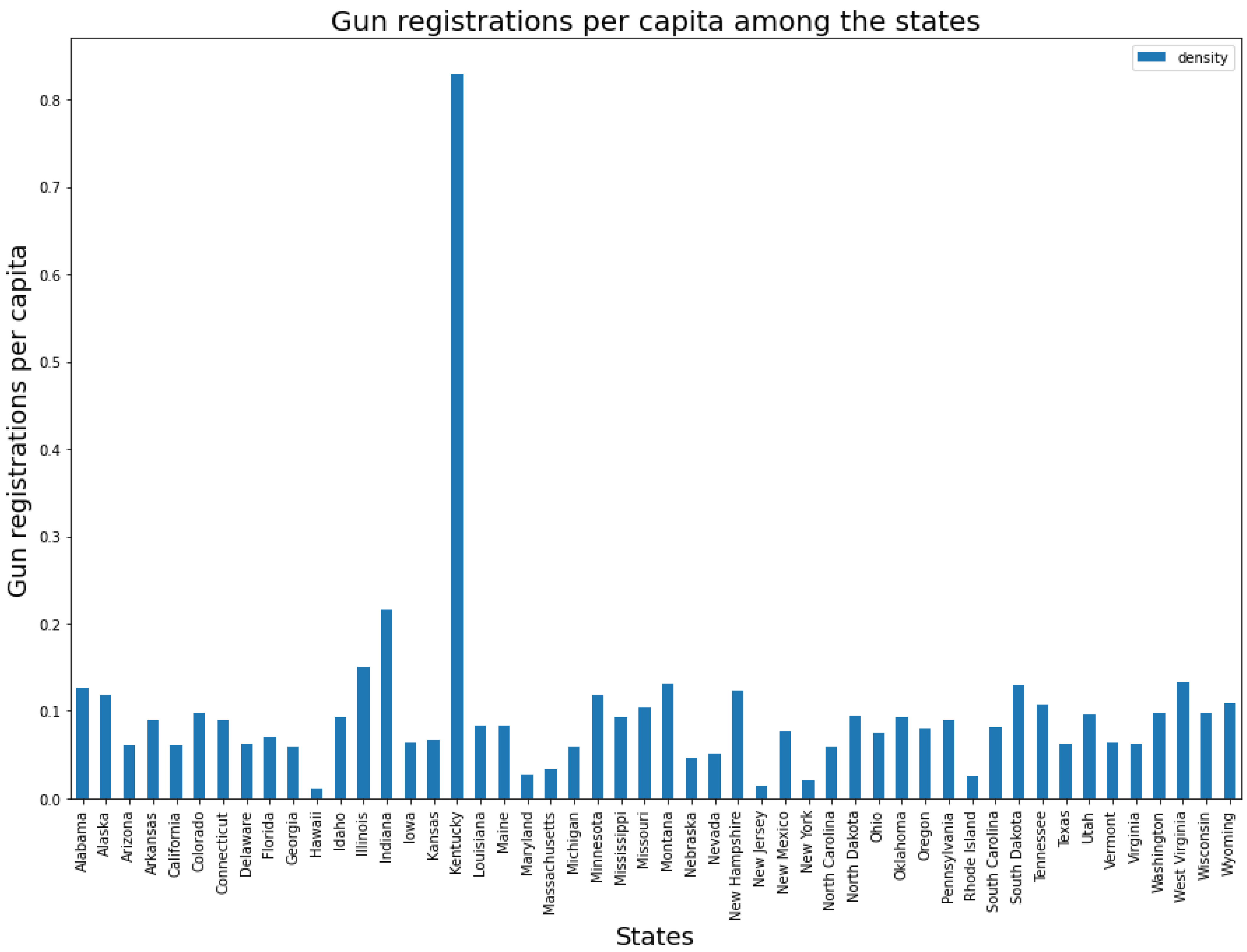
```
# We'll create a new column to calculate the gun registeration per capita in

combined['density']=combined['totals']/combined['Population estimates, July 1, 2016,  (V2016)']
```

In [ ]:

```
# Then we will plot a gun per capita in every state chart
combined.plot(y=['density'],kind='bar',figsize=(15,10));
plt.title('Gun registrations per capita among the states', fontsize=20)
plt.xlabel('States', fontsize=18)
plt.ylabel('Gun registrations per capita', fontsize=18)
```

Out[ ]:

```
Text(0, 0.5, 'Gun registrations per capita')
```



From the chart we can see Kuntucky seems to lead the highest registered guns per capita with Indiana in second place

California and Texas high gun registerations from the previous questions may be due to high population as we see here they have receeded to lower ranks when checked across the population

Conclusions

From our EDA we can see that gun registeration was steady from 1999 till 2004 then it increased over the years until it reached its peak on 2016 then decreased.

At the same time the long guns were more popular from 1999 with the handguns closing the gap untill 2013-2014 when the handguns became more popular and the other types of guns slightly rise in popularity but still far away from long guns and handguns.

Kentucky, California and Texas seems to be the highest in gun registeration However that turned out to be related to population as we checked them again for the year 2016 against the population. Only Kentucky was leading the chart with Indiana in second place.

Limitations

- The Gun data has the states as well as the territories making 55 however the census data has only the 50 states so had to drop the 5 extra when merging
- The background check for a gun does not represent gun sales by any means therefore this analysis only refers to the registeration requests
- the census data has mostly 2016's data and some 2010's so the comparison is not reliable in comparison to one that would have the data from all the years as the gun data ones
- some data from NICS are supressed as their publication was not possible

In [ ]: