

Project: Investigate the FBI Gun Dataset

Table of Contents

- [Introduction](#)
- [Data Wrangling](#)
- [Exploratory Data Analysis](#)
- [Conclusions](#)

Introduction

Key notes: "The data comes from the FBI's National Instant Criminal Background Check System. The NICS is used by to determine whether a prospective buyer is eligible to buy firearms or explosives. Gun shops call into this system to ensure that each customer does not have a criminal record or isn't otherwise ineligible to make a purchase. The data has been supplemented with state level data from census.gov.

The NICS data is found in one sheet of an .xlsx file. It contains the number of firearm checks by month, state, and type.

The U.S. census data is found in a .csv file. It contains several variables at the state level. Most variables just have one data point per state (2016), but a few have data for more than one year."

Questions to explore:

- [1. The highest purchases record happened in which state for the persons under 18 years, percent on April 1, 2010?](#)
- [2. In which state did asian alone buy minmum number of guns in terms of percent \(>0\), July 1, 2016?](#)
- [3. What is the total annual payroll of all the states \(\\$, 1000\) in 2015?](#)
- [4. What is the average revenue of firms of all the states in 2012?](#)
- [5. What census data is most associated with high gun per capita?](#)
- [6. Which states have had the highest growth in gun registrations?](#)
- [7. What is the overall trend of gun purchases?](#)
- [8. How many guns were registered in total in January?](#)
- [9. How many guns were registered in total in September, 2003?](#)
- [10. What type of gun has highest quantity, and the relationship to totals?](#)
- [11. What is the sum of registered gun in each state over time?](#)

In [32]:

```
# Set up import statements for all of the packages that are planed to use;  
# Include a 'magic word' so that visualizations are plotted;  
# call on dataframe to display the first 5 rows.
```

```
import pandas as pd  
import numpy as np  
import datetime  
from statistics import mode  
% matplotlib inline  
import matplotlib.pyplot as plt  
%config InlineBackend.figure_format = 'retina'  
import seaborn as sns  
sns.set_style('darkgrid')  
df = pd.read_csv('U.S. Census Data.csv', sep=',')
```

Data Wrangling

Key notes: In this section of the report, the following work will be done: load the data; check for cleanliness; trim and clean dataset for analysis.

General Properties

In [33]:

```
# Load data and print out a few lines  
  
df.head()
```

Out[33] :

	Fact	Fact Note	Alabama	Alaska	Arizona	Arkansas	California	Colorado	Co
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	3,5
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	3,5
2	Population, percent change - April 1, 2010 (es...	NaN	1.70%	4.50%	8.40%	2.50%	5.40%	10.20%	0.1
3	Population, Census, April 1, 2010	NaN	4,779,736	710,231	6,392,017	2,915,918	37,253,956	5,029,196	3,5
4	Persons under 5 years, percent, July 1, 2016, ...	NaN	6.00%	7.30%	6.30%	6.40%	6.30%	6.10%	5.2

5 rows × 52 columns

In [34]:

```
# Reading an Excel file in python using pandas  
# call on dataframe to display the first 5 rows
```

```
xl = pd.ExcelFile('gun_data.xlsx')
```

```
xl.sheet_names  
[u'Sheet1']
```

```
df1 = xl.parse("Sheet1")  
df1.head()
```

Out[34]:

	month	state	permit	permit_recheck	handgun	long_gun	other	multiple	adl
0	2017-09	Alabama	16717.0	0.0	5734.0	6320.0	221.0	317	0.0
1	2017-09	Alaska	209.0	2.0	2320.0	2930.0	219.0	160	0.0
2	2017-09	Arizona	5069.0	382.0	11063.0	7946.0	920.0	631	0.0
3	2017-09	Arkansas	2935.0	632.0	4347.0	6063.0	165.0	366	51.
4	2017-09	California	57839.0	0.0	37165.0	24581.0	2984.0	0	0.0

5 rows × 27 columns

In [35]:

```
# return a tuple of the dimensions of the dataframe.
```

```
df.shape, df1.shape
```

Out[35]:

```
((85, 52), (12485, 27))
```

In [36]:

```
# print the column labels in the dataframe.
```

```
for i, v in enumerate(df.columns):  
    print(i, v)
```

0 Fact
1 Fact Note
2 Alabama
3 Alaska
4 Arizona
5 Arkansas
6 California
7 Colorado
8 Connecticut
9 Delaware
10 Florida
11 Georgia
12 Hawaii
13 Idaho
14 Illinois
15 Indiana
16 Iowa
17 Kansas
18 Kentucky
19 Louisiana
20 Maine
21 Maryland
22 Massachusetts
23 Michigan
24 Minnesota
25 Mississippi
26 Missouri
27 Montana
28 Nebraska
29 Nevada
30 New Hampshire
31 New Jersey
32 New Mexico
33 New York
34 North Carolina
35 North Dakota
36 Ohio
37 Oklahoma
38 Oregon
39 Pennsylvania
40 Rhode Island
41 South Carolina
42 South Dakota
43 Tennessee
44 Texas
45 Utah
46 Vermont
47 Virginia
48 Washington
49 West Virginia
50 Wisconsin
51 Wyoming

In [37]:

```
for i, v in enumerate(df1.columns):  
    print(i, v)
```

```
0 month  
1 state  
2 permit  
3 permit_recheck  
4 handgun  
5 long_gun  
6 other  
7 multiple  
8 admin  
9 prepawn_handgun  
10 prepawn_long_gun  
11 prepawn_other  
12 redemption_handgun  
13 redemption_long_gun  
14 redemption_other  
15 returned_handgun  
16 returned_long_gun  
17 returned_other  
18 rentals_handgun  
19 rentals_long_gun  
20 private_sale_handgun  
21 private_sale_long_gun  
22 private_sale_other  
23 return_to_seller_handgun  
24 return_to_seller_long_gun  
25 return_to_seller_other  
26 totals
```

In [38]:

```
# return the datatypes of the columns.
```

```
df.dtypes
```

Out[38]:

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

In [39]:

```
df1.dtypes
```

Out[39]:

month	object
state	object
permit	float64
permit_recheck	float64
handgun	float64
long_gun	float64
other	float64
multiple	int64
admin	float64
prepawn_handgun	float64
prepawn_long_gun	float64
prepawn_other	float64
redemption_handgun	float64
redemption_long_gun	float64
redemption_other	float64
returned_handgun	float64
returned_long_gun	float64
returned_other	float64
rentals_handgun	float64
rentals_long_gun	float64
private_sale_handgun	float64
private_sale_long_gun	float64
private_sale_other	float64
return_to_seller_handgun	float64
return_to_seller_long_gun	float64
return_to_seller_other	float64
totals	int64
dtype:	object

In [40]:

```
# check for duplicates in the data.
```

```
sum(df.duplicated())
```

Out[40]:

3

In [41]:

```
# check for duplicates in the data.
```

```
sum(df1.duplicated())
```

Out[41]:

0

In [42]:

```
# check if any value is NaN in DataFrame and in how many columns
```

```
df.isnull().any().any(), sum(df.isnull().any())
```

Out[42]:

(True, 52)

In [43]:

```
# check NaN exist in which column
```

```
df.isnull().any()
```

Out[43]:

Fact	True
Fact Note	True
Alabama	True
Alaska	True
Arizona	True
Arkansas	True
California	True
Colorado	True
Connecticut	True
Delaware	True
Florida	True
Georgia	True
Hawaii	True
Idaho	True
Illinois	True
Indiana	True
Iowa	True
Kansas	True
Kentucky	True
Louisiana	True
Maine	True
Maryland	True
Massachusetts	True
Michigan	True
Minnesota	True
Mississippi	True
Missouri	True

Montana	True
Nebraska	True
Nevada	True
New Hampshire	True
New Jersey	True
New Mexico	True
New York	True
North Carolina	True
North Dakota	True
Ohio	True
Oklahoma	True
Oregon	True
Pennsylvania	True
Rhode Island	True
South Carolina	True
South Dakota	True
Tennessee	True
Texas	True
Utah	True
Vermont	True
Virginia	True
Washington	True
West Virginia	True
Wisconsin	True
Wyoming	True
dtype:	bool

In [44]:

```
df1.isnull().any().any(), sum(df1.isnull().any())
```

Out[44]:

```
(True, 23)
```

In [45]:

```
df1.isnull().any()
```

Out[45]:

month	False
state	False
permit	True
permit_recheck	True
handgun	True
long_gun	True
other	True
multiple	False
admin	True
prepawn_handgun	True
prepawn_long_gun	True
prepawn_other	True
redemption_handgun	True
redemption_long_gun	True
redemption_other	True
returned_handgun	True
returned_long_gun	True
returned_other	True
rentals_handgun	True
rentals_long_gun	True
private_sale_handgun	True
private_sale_long_gun	True
private_sale_other	True
return_to_seller_handgun	True
return_to_seller_long_gun	True
return_to_seller_other	True
totals	False

dtype: bool

In [46]:

```
# displays a concise summary of the dataframe;  
# including the number of non-null values in each column.
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 85 entries, 0 to 84  
Data columns (total 52 columns):  
Fact                80 non-null object  
Fact Note           28 non-null object  
Alabama             65 non-null object  
Alaska              65 non-null object  
Arizona             65 non-null object  
Arkansas            65 non-null object  
California          65 non-null object  
Colorado            65 non-null object
```

Connecticut	65	non-null	object
Delaware	65	non-null	object
Florida	65	non-null	object
Georgia	65	non-null	object
Hawaii	65	non-null	object
Idaho	65	non-null	object
Illinois	65	non-null	object
Indiana	65	non-null	object
Iowa	65	non-null	object
Kansas	65	non-null	object
Kentucky	65	non-null	object
Louisiana	65	non-null	object
Maine	65	non-null	object
Maryland	65	non-null	object
Massachusetts	65	non-null	object
Michigan	65	non-null	object
Minnesota	65	non-null	object
Mississippi	65	non-null	object
Missouri	65	non-null	object
Montana	65	non-null	object
Nebraska	65	non-null	object
Nevada	65	non-null	object
New Hampshire	65	non-null	object
New Jersey	65	non-null	object
New Mexico	65	non-null	object
New York	65	non-null	object
North Carolina	65	non-null	object
North Dakota	65	non-null	object
Ohio	65	non-null	object
Oklahoma	65	non-null	object
Oregon	65	non-null	object
Pennsylvania	65	non-null	object
Rhode Island	65	non-null	object
South Carolina	65	non-null	object
South Dakota	65	non-null	object
Tennessee	65	non-null	object
Texas	65	non-null	object
Utah	65	non-null	object
Vermont	65	non-null	object
Virginia	65	non-null	object
Washington	65	non-null	object
West Virginia	65	non-null	object
Wisconsin	65	non-null	object
Wyoming	65	non-null	object

dtypes: object(52)

memory usage: 34.6+ KB

In [47]:

```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12485 entries, 0 to 12484
Data columns (total 27 columns):
month                12485 non-null object
state                12485 non-null object
permit              12461 non-null float64
permit_recheck      1100 non-null float64
handgun              12465 non-null float64
long_gun             12466 non-null float64
other                5500 non-null float64
multiple             12485 non-null int64
admin                12462 non-null float64
prepawn_handgun      10542 non-null float64
prepawn_long_gun     10540 non-null float64
prepawn_other        5115 non-null float64
redemption_handgun   10545 non-null float64
redemption_long_gun  10544 non-null float64
redemption_other     5115 non-null float64
returned_handgun     2200 non-null float64
returned_long_gun    2145 non-null float64
returned_other       1815 non-null float64
rentals_handgun      990 non-null float64
rentals_long_gun     825 non-null float64
private_sale_handgun 2750 non-null float64
private_sale_long_gun 2750 non-null float64
private_sale_other    2750 non-null float64
return_to_seller_handgun 2475 non-null float64
return_to_seller_long_gun 2750 non-null float64
return_to_seller_other 2255 non-null float64
totals                12485 non-null int64
dtypes: float64(23), int64(2), object(2)
memory usage: 2.6+ MB
```

In [48]:

```
# Generates descriptive statistics, excluding NaN values.  
  
df.describe()
```

Out[48]:

	Fact	Fact Note	Alabama	Alaska	Arizona	Arkansas	California	Colorado	Connecticut
count	80	28	65	65	65	65	65	65	65
unique	80	15	65	64	64	64	63	64	63
top	1	(c)	16.10%	7.30%	50.30%	50.90%	6.80%	3.30%	5.70%
freq	1	6	1	2	2	2	2	2	2

4 rows × 52 columns

In [49]:

```
df1.describe()
```

Out[49]:

	permit	permit_recheck	handgun	long_gun	other
count	12461.000000	1100.000000	12465.000000	12466.000000	5500.000000
mean	6413.629404	1165.956364	5940.881107	7810.847585	360.471636
std	23752.338269	9224.200609	8618.584060	9309.846140	1349.478273
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	865.000000	2078.250000	17.000000
50%	518.000000	0.000000	3059.000000	5122.000000	121.000000
75%	4272.000000	0.000000	7280.000000	10380.750000	354.000000
max	522188.000000	116681.000000	107224.000000	108058.000000	77929.000000

8 rows × 25 columns

Data Cleaning

In [50]:

```
# drop duplicates  
# Confirm changes  
  
df.drop_duplicates(inplace=True)  
sum(df.duplicated())
```

Out[50]:

0

In [51]:

```
df1.drop_duplicates(inplace=True)  
sum(df.duplicated())
```

Out[51]:

0

In [52]:

```
# Change column name in df1 into lower case for the convenience of analysis  
# Confirm changes  
  
df.rename(columns = lambda x: x.lower(), inplace = True)  
df.head()
```

Out[52] :

	fact	fact note	alabama	alaska	arizona	arkansas	california	colorado	cor
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	3,5
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	3,5
2	Population, percent change - April 1, 2010 (es...	NaN	1.70%	4.50%	8.40%	2.50%	5.40%	10.20%	0.1
3	Population, Census, April 1, 2010	NaN	4,779,736	710,231	6,392,017	2,915,918	37,253,956	5,029,196	3,5
4	Persons under 5 years, percent, July 1, 2016, ...	NaN	6.00%	7.30%	6.30%	6.40%	6.30%	6.10%	5.2

5 rows × 52 columns

In [53]:

```
# As the NaN values are of string type therefore they can't be treated by filling with means
# since they don't affect the arithmetic calculation nor statistical analysis
# so it is better to replace those NaN values with a common string type value which doesn't indicate anything
# For the numerical type of NaN, as each row has specific meaning, thus we can't fill them with mean

# As for df, numerical type of data was misrepresented as string type, thus first task is to convert them into float
# Skip the first 2 columns as they should be string type, so leave them unchanged

col = df.iloc[:,2:].columns
for c in col:
    df[c] = df[c].str.extract('(\d+)').astype(float)

# confirm changes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
Int64Index: 82 entries, 0 to 84
```

```
Data columns (total 52 columns):
```

fact	80 non-null	object
fact note	28 non-null	object
alabama	65 non-null	float64
alaska	64 non-null	float64
arizona	65 non-null	float64
arkansas	65 non-null	float64
california	65 non-null	float64
colorado	65 non-null	float64
connecticut	65 non-null	float64
delaware	65 non-null	float64
florida	65 non-null	float64
georgia	65 non-null	float64
hawaii	64 non-null	float64
idaho	65 non-null	float64
illinois	65 non-null	float64
indiana	65 non-null	float64
iowa	65 non-null	float64
kansas	65 non-null	float64
kentucky	65 non-null	float64
louisiana	65 non-null	float64
maine	64 non-null	float64
maryland	65 non-null	float64
massachusetts	65 non-null	float64
michigan	64 non-null	float64
minnesota	65 non-null	float64
mississippi	65 non-null	float64
missouri	65 non-null	float64
montana	65 non-null	float64

```

nebraska          65 non-null float64
nevada            65 non-null float64
new hampshire     65 non-null float64
new jersey        65 non-null float64
new mexico        65 non-null float64
new york          65 non-null float64
north carolina    65 non-null float64
north dakota      65 non-null float64
ohio              65 non-null float64
oklahoma          65 non-null float64
oregon            65 non-null float64
pennsylvania      65 non-null float64
rhode island      65 non-null float64
south carolina    65 non-null float64
south dakota      65 non-null float64
tennessee         65 non-null float64
texas             65 non-null float64
utah              65 non-null float64
vermont           64 non-null float64
virginia          65 non-null float64
washington        65 non-null float64
west virginia     64 non-null float64
wisconsin         65 non-null float64
wyoming           64 non-null float64
dtypes: float64(50), object(2)
memory usage: 34.0+ KB

```

```

/Users/shilinli/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:11: FutureWarning: currently extract(expand=None) means expand=False (return Index/Series/DataFrame) but in a future version of pandas this will be changed to expand=True (return DataFrame)
  # This is added back by InteractiveShellApp.init_path()

```

In [54]:

```

# Replace the all NaN in df with 'No Record'

df.fillna('No record', inplace = True)

# Confirm changes

df.isnull().any()

```

Out[54]:

```

fact                False
fact note           False
alabama             False
alaska              False
arizona             False
arkansas            False
california          False
colorado            False
connecticut         False

```

delaware	False
florida	False
georgia	False
hawaii	False
idaho	False
illinois	False
indiana	False
iowa	False
kansas	False
kentucky	False
louisiana	False
maine	False
maryland	False
massachusetts	False
michigan	False
minnesota	False
mississippi	False
missouri	False
montana	False
nebraska	False
nevada	False
new hampshire	False
new jersey	False
new mexico	False
new york	False
north carolina	False
north dakota	False
ohio	False
oklahoma	False
oregon	False
pennsylvania	False
rhode island	False
south carolina	False
south dakota	False
tennessee	False
texas	False
utah	False
vermont	False
virginia	False
washington	False
west virginia	False
wisconsin	False
wyoming	False
dtype: bool	

In [55]:

```
coll = df1.iloc[:,np.r_[2:7, 8:26]].columns
for c in coll:
    c_mean = df1[c].mean()
    df1[c].fillna(c_mean, inplace = True)

# Confirm changes

df1.isnull().any()
```

Out[55]:

month	False
state	False
permit	False
permit_recheck	False
handgun	False
long_gun	False
other	False
multiple	False
admin	False
prepawn_handgun	False
prepawn_long_gun	False
prepawn_other	False
redemption_handgun	False
redemption_long_gun	False
redemption_other	False
returned_handgun	False
returned_long_gun	False
returned_other	False
rentals_handgun	False
rentals_long_gun	False
private_sale_handgun	False
private_sale_long_gun	False
private_sale_other	False
return_to_seller_handgun	False
return_to_seller_long_gun	False
return_to_seller_other	False
totals	False
dtype:	bool

In [56]:

```
# Convert string into datetime format in df1

df1.month = pd.to_datetime(df1['month'], errors='coerce')

# Confirm changes

df1.head()
```

Out[56]:

	month	state	permit	permit_recheck	handgun	long_gun	other	multiple	adl
0	2017-09-01	Alabama	16717.0	0.0	5734.0	6320.0	221.0	317	0.0
1	2017-09-01	Alaska	209.0	2.0	2320.0	2930.0	219.0	160	0.0
2	2017-09-01	Arizona	5069.0	382.0	11063.0	7946.0	920.0	631	0.0
3	2017-09-01	Arkansas	2935.0	632.0	4347.0	6063.0	165.0	366	51.
4	2017-09-01	California	57839.0	0.0	37165.0	24581.0	2984.0	0	0.0

5 rows × 27 columns

Exploratory Data Analysis

Research Question 1: The highest purchases record happened in which state for the persons under 18 years, percent on April 1, 2010?

In [57]:

```
# Find out which state had such max value

df.iloc[7, 2:].idxmax(axis = 1)
```

Out[57]:

'utah'

In [58]:

```
# Print out the exact number
```

```
df.iloc[7, 2:].loc['utah']
```

Out[58]:

31.0

Utah state had highest purchases record for persons under 18 years, percent on April 1, 2010, and the percent is 31.

Research Question 2: In which state did asian alone buy minimum number of guns in terms of percent (>0), July 1, 2016?

In [59]:

```
# select the target state
```

```
asi_jul_16 = df.iloc[15, 2:]
```

```
# select the state whose total annual payroll is above 0
```

```
for t in asi_jul_16.index:  
    if asi_jul_16.loc[t] == 0:  
        asi_jul_16.drop([t], inplace = True)
```

```
# Print out the index of which had the minimum value
```

```
asi_jul_16.idxmin()
```

Out[59]:

'alabama'

In [60]:

```
# Print out the exact number
```

```
asi_jul_16.loc['alabama']
```

Out[60]:

1.0

In alabama state, asian alone bought the minimum number of gun in terms of percent, which is 1%.

Research Question 3: What is the total annual payroll of all the states (\$, 1000) in 2015?

In [61]:

```
df.iloc[52, 2:].sum()
```

Out[61]:

```
1531393139.0
```

The total annual payroll of att states in 2015 is 1531393139 (\$, 1000).

Research Question 4: What is the average revenue of firms of all the states in 2012?

In [62]:

```
df.iloc[55, 2:].mean()
```

Out[62]:

```
133749.26000000001
```

The average revenue of firms of all the states in 2012 is around 133749.26 dollar.

Research Question 5: What census data is most associated with high gun per capita?

In [63]:

```
# Synchronize both dataframe at 2010
```

```
state_df1 = df1.query('month == "2010-04-01"').state.str.lower().tolist()
state_df = df.iloc[3, 2:].index.tolist()
```

In [64]:

```
# Compare the element difference in column of 'state'
```

```
miss_state = []
def miss_states(state):
    for s in state:
        if s not in state_df:
            miss_state.append(s)
    return miss_state
```

```
miss_states(state_df1)
```

Out[64]:

```
['district of columbia',
 'guam',
 'mariana islands',
 'puerto rico',
 'virgin islands']
```

In [65]:

```
# Convert all vaules in column of 'state' from df1 in lower case in order to match
# the format in column of 'state' from df for later calculatation
# Confirm changes
```

```
df1['state'] = df1.state.str.lower()
```

In [66]:

```
# Use query to select common elements in columns of 'state' from both dataframe
```

```
gun_tot_2010 = df1.query('month == "2010-04-01" & state != @miss_state')
```

In [67]:

```
# Use assertation function to confirm 'state' columns' elements from both dataframe are identical
```

```
assert(gun_tot_2010.state.tolist() == df.iloc[3, 2:].index.tolist())
```


In [68]:

```
# Set index to be state in order to do arithmetic calculation  
  
gun_tot_2010.set_index('state', inplace = True)
```

In [69]:

```
# Calcluate the high gun per capita  
  
avg_2010 = gun_tot_2010.totals/df.iloc[3, 2:]
```

In [70]:

```
# Find out the index which points to the highest value  
  
avg_2010.idxmax()
```

Out[70]:

'utah'

In [71]:

```
# Print out the value  
  
avg_2010.loc['utah']
```

Out[71]:

54695.5

The highest gun per capita was 54695.5, that occurred at utah in 2010.

In [72]:

```
# Same for 2016  
# Synchronize both dataframe at 2016  
  
state_df1_2016 = df1.query('month == "2016-07-01"').state.str.lower().tolist()  
state_df_2016 = df.iloc[0, 2:].index.tolist()
```

In [73]:

```
# Compare the element difference in columns of 'state'
```

```
miss_state_2016 = []  
def miss_states(state):  
    for s in state:  
        if s not in state_df_2016:  
            miss_state_2016.append(s)  
    return miss_state_2016
```

```
miss_states(state_df1_2016)
```

Out[73]:

```
['district of columbia',  
 'guam',  
 'mariana islands',  
 'puerto rico',  
 'virgin islands']
```

In [74]:

```
# Use query to select common elements in columns of 'state' from both dataframe
```

```
gun_tot_2016 = df1.query('month == "2016-07-01" & state != @miss_state')
```

In [75]:

```
# Use assertation function to confirm 'state' column's elements from both dataframe are identical
```

```
assert(gun_tot_2016.state.tolist() == df.iloc[0, 2:].index.tolist())
```

In [76]:

```
# Set index to be state in order to do arithmetic calculation
```

```
gun_tot_2016.set_index('state', inplace = True)
```

In [77]:

```
# Calcluate the high gun per capita
```

```
avg_2016 = gun_tot_2016.totals/df.iloc[0, 2:]
```

In [78]:

```
# Find out the index which points to the highest value
```

```
avg_2016.idxmax()
```

Out[78]:

```
'kentucky'
```

In [79]:

```
# Print out the value
```

```
avg_2010.loc['kentucky']
```

Out[79]:

```
52815.25
```

The highest gun per capita was 52815.25, that occurred at 'kentucky' in 2016.

Research Question 6: Which states have had the highest growth in gun registrations?

In [80]:

```
# Groupby time, state and sum of totals
```

```
gun_alltime = df1.groupby(['month', 'state'])['totals'].sum()
```

In [81]:

```
# Find out the earliest and latest registration date
```

```
cur_date = df1['month'].max()
```

```
ear_date = df1['month'].min()
```

In [82]:

```
# The amount of registred guns from lastest subtract the earliest  
  
gun_grow_tot = gun_alltime.loc[cur_date] - gun_alltime.loc[ear_date]  
  
# Find out the index of maximum value  
  
gun_grow_tot.idxmax()
```

Out[82]:

'kentucky'

In [83]:

```
# Print out the exact numbers  
  
gun_grow_tot.loc['kentucky']
```

Out[83]:

397866

'kentucky' have had the highest growth in gun registrations over time, and the total registered number of guns is 397866 to date.

Research Question 7: What is the overall trend of gun purchases?

In [84]:

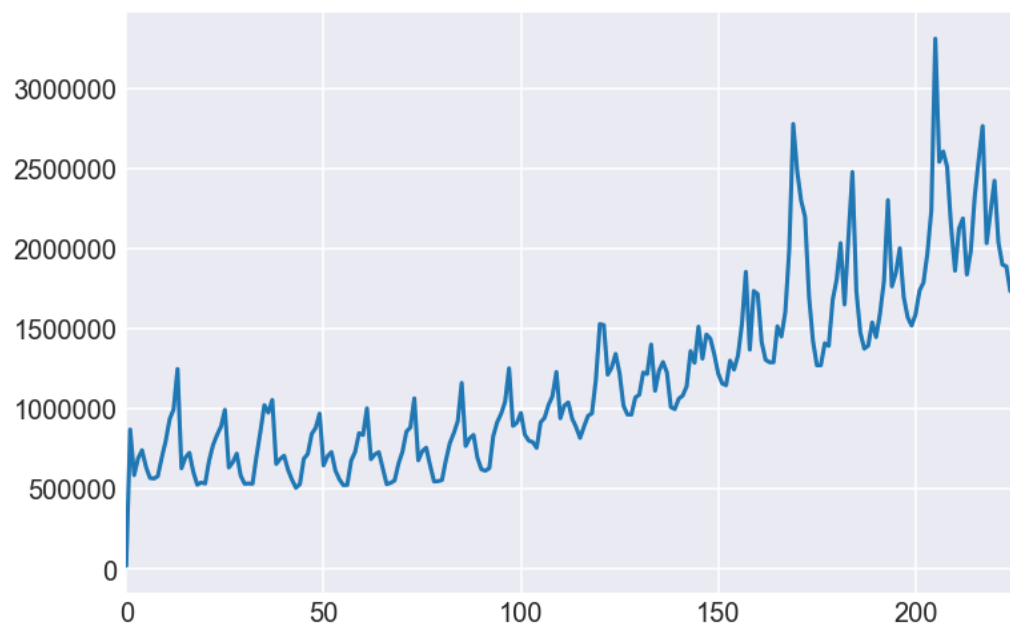
```
# Groupby time and sum of totals
# This function is intended to be used with data where observations are
# nested within sampling units that were measured at multiple timepoints

gun_trend = df1.groupby(['month'])['totals'].sum()

ax = sns.tsplot(data = gun_trend, err_style="unit_traces");
```

/Users/shilinli/anaconda3/lib/python3.6/site-packages/seaborn/timeseries.py:183: UserWarning: The tsplot function is deprecated and will be removed or replaced (in a substantially altered version) in a future release.

```
warnings.warn(msg, UserWarning)
```



The overall trend is increasing, the speed is becoming faster over time.

Research Question 8: How many guns were registered in total in January?

In [85]:

```
# Extract month from datetime column (month)
# Copy the dataframe and add a new column with this newly generated month

month_data = df1.month.dt.strftime("%B")

df_test = df1.copy()

df_test['registered_month'] = month_data
```

In [86]:

```
# Find all the rows in January and February and sum the totals  
# Use substraction to find the answer  
  
feb_gun = df_test.query('registered_month == "February"')  
jan_gun = df_test.query('registered_month == "January"')  
feb_gun.totals.sum() - jan_gun.totals.sum()
```

Out[86]:

1792105

The total registered guns in January was 1792105 pieces.

Research Question 9: How many guns were registered in total in September, 2003?

In [87]:

```
# Census were recorded on every 1st day of each month  
# Target the desired date  
# Find out the number  
  
tot_oct01_03 = df1.query('month == "2003-10-01"')  
tot_sep01_03 = df1.query('month == "2003-09-01"')  
tot_oct01_03.groupby(['month'])['totals'].sum().tolist()[0] - \  
tot_sep01_03.groupby(['month'])['totals'].sum().tolist()[0]
```

Out[87]:

117064

The total registred guns in September of 2003 were 117064 pieces.

Research Question 10: What type of gun has highest quantity, and the relationship to totals?

In [88]:

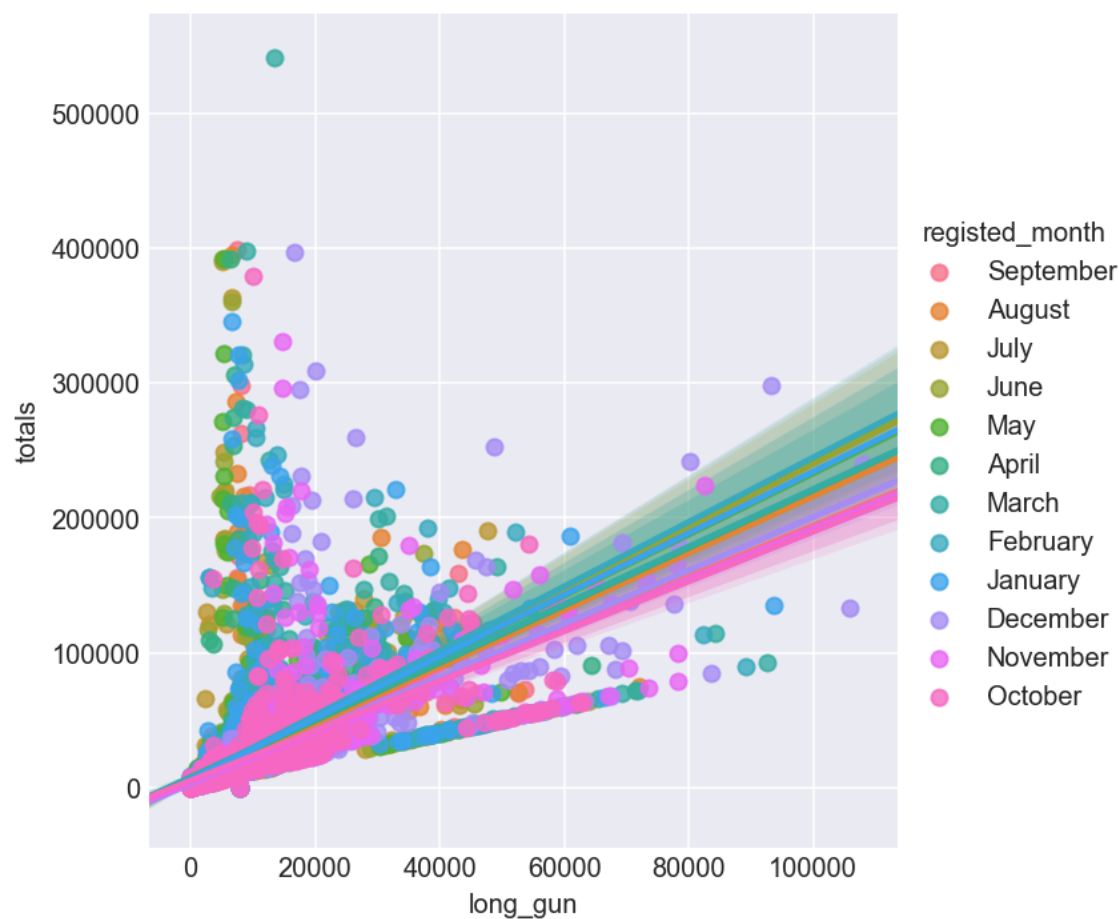
```
gun_type = {}  
col_state = df1.columns[2:25]  
  
for c in col_state:  
    gun_type[c] = df1[c].sum()  
  
max(gun_type, key=gun_type.get)
```

Out[88]:

'long_gun'

In [89]:

```
sns.lmplot(x = 'long_gun', y = 'totals', hue = 'registered_month', data = df_test)  
;
```

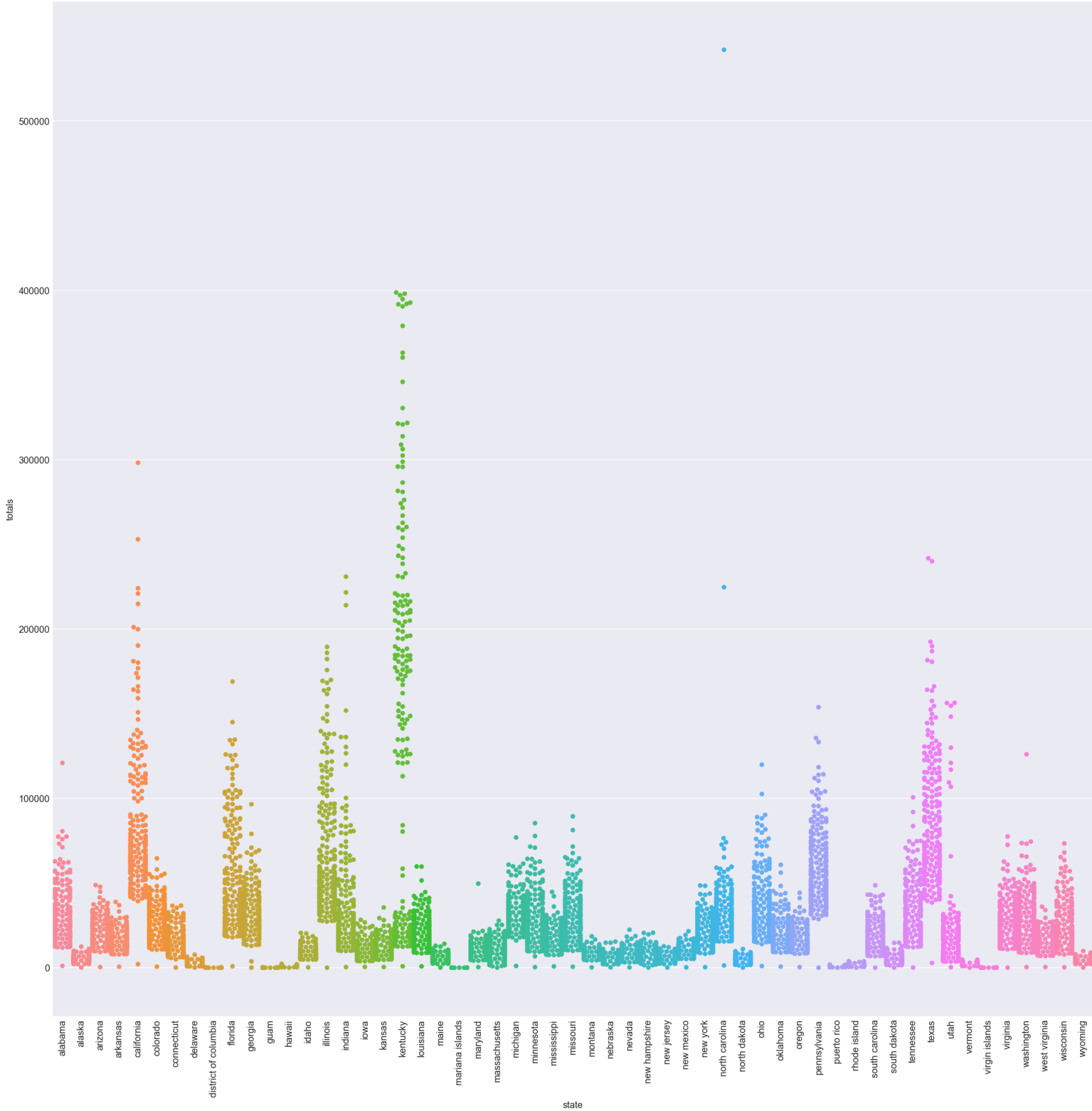


Long gun is highest registered type of gun in number among the others, it is positively correlated with totals. The estimated linear regression is shown as the blue line, the estimates varies in the light blue shade with 95% confident level.

Research Question 11: What is the sum of registered gun in each state over time?

In [90]:

```
plt.subplots(figsize=(20,20))
plt.xticks(rotation=90);
sns.swarmplot(x='state', y='totals', data=df1);
```



Conclusions

In current study, a good amount of profound analysis has been carried out. Prior to each step, detailed instructions were given and interpretations were also provided afterwards. The dataset included 2 tables, but they have to be loaded by different measures. The data was ranging from 1998 to 2017, which consisted of detailed information of registered gun. Based on such substantial data, the analysis would be more reliable as opposed to small scale analysis.

The limitations of current study were obvious as well, data was separated into two tables which could affect the process of analysis. On the other hand, the population estimation were only recorded for 2010 and 2016, which limit some analysis to a small range, same for many other parameters, such as "Foreign born persons, percent", "Veterans, 2011-2015", etc.

In [92]:

```
from subprocess import call  
call(['python', '-m', 'nbconvert', 'Investigate_FBI_Gun_Dataset.ipynb'])
```

Out[92]:

0