FBI Gun Data

March 21, 2018

1 Smoking Gun? : Re-examining the relationship between FBI background checks and state-level census data

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Introduction

In this report, I will be exploring what census data tells us about gun purchases across the US. The gun data comes from 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 state level census data comes from census.gov.

I downloaded the NICS data in .xlxs format from the Udacity project site and used Excel to save it as a csv file so that I could use pandas to manipulate it. The census data was already in .csv format so this step was unneccesary. I combined the two files to one csv to make working with them easier.

For this project, I wanted to answer the questions that are listed below:

```
<li> Which kinds of guns are people applying permits for? </li>
<li> How does redemption data compare between the types of firearms overall? </li>
<li> How does the percentage of people with Bachelor's degree affect permit applications? </li
<li> To Shoot or to Build: Comparing Business permits vs Firearm permits </li>
<li> Which states have had the highest growth in gun registrations? </li>
```

Tools

I used pandas and numpy to make working with the .csv's easier and more efficient. I also used matplotlib to plot graphs showing the relationships between the various variables and added seaborn to make the graphs visually appealing. All plots appeared inline to make working with the data quick and presentable in report form.

```
In [1]: import datetime as dt
        import pandas as pd
        import numpy as np
```

```
import matplotlib.pyplot as plt
import seaborn as sns
% matplotlib inline
```

Data Wrangling

In this section of the report, I loaded in the data from the csv documents, checked for cleanliness, and then trimmed and cleaned the dataset for analysis. Cleaning decisions I made are explained in the cells adjacent to the code.

1.1.1 General Properties of the dataset

In [2]:
```
#Read in the csv files
census_data = pd.read_csv('census.csv')
gun_data = pd.read_csv('gun_data.csv')
```

In [3]:
```
#Print out first rows of data frame to make sure the data was read in correctly
census_data.head()
```

Out[3]:

	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	4863300	741894	6931071	2988248	39250017	5540545	3576452	952065	...	865454	6651194	27862596	3051217	624594	8411808	7288000	1831102	5778708	585501
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 x 52 columns]

In [4]:
```
gun_data.head()
```

Out[4]:

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

	multiple	admin	prepawn_handgun	...	returned_other	rentals_handgun	\
0	317	0.0	15.0	...	0.0	0.0	
1	160	0.0	5.0	...	0.0	0.0	
2	631	0.0	13.0	...	0.0	0.0	
3	366	51.0	12.0	...	0.0	0.0	
4	0	0.0	0.0	...	0.0	0.0	

	rentals_long_gun	private_sale_handgun	private_sale_long_gun	\
0	0.0	9.0	16.0	
1	0.0	17.0	24.0	
2	0.0	38.0	12.0	
3	0.0	13.0	23.0	
4	0.0	0.0	0.0	

	private_sale_other	return_to_seller_handgun	return_to_seller_long_gun	\
0	3.0	0.0	0.0	
1	1.0	0.0	0.0	
2	2.0	0.0	0.0	
3	0.0	0.0	2.0	
4	0.0	0.0	0.0	

	return_to_seller_other	totals
0	3.0	32019
1	0.0	6303
2	0.0	28394
3	1.0	17747
4	0.0	123506

[5 rows x 27 columns]

In [5]:
```
#What does the data look like
census_data.shape
```

Out[5]: (85, 52)

In [6]:
```
gun_data.shape
```

Out[6]: (12485, 27)

In [7]:
```
#What are the summary statistics
census_data.describe();
gun_data.describe();
```

1.1.2 Data Cleaning

```
In [8]: #Drop columns in gun_data that aren't relevant to the questions I am trying to answer
        gun_data.drop(['permit_recheck', 'multiple','admin','prepawn_handgun','prepawn_long_gu

In [9]: gun_data.head() #Confirm that data was successfully dropped
```

Out[9]:

	month	state	permit	handgun	long_gun	other	\
0	2017-09	Alabama	16717.0	5734.0	6320.0	221.0	
1	2017-09	Alaska	209.0	2320.0	2930.0	219.0	
2	2017-09	Arizona	5069.0	11063.0	7946.0	920.0	
3	2017-09	Arkansas	2935.0	4347.0	6063.0	165.0	
4	2017-09	California	57839.0	37165.0	24581.0	2984.0	

	redemption_handgun	redemption_long_gun
0	1378.0	1262.0
1	200.0	154.0
2	1474.0	748.0
3	1296.0	1824.0
4	535.0	397.0

```
In [117]: gun_data['month'] = pd.to_datetime(gun_data['month']) #Convert month to datetime obj

In [10]: #Drop columns in census that aren't relevant to my questions
         census_data.drop(['Fact Note'] ,axis=1, inplace=True) # Drop the Fact Note Column sin

In [11]: census_data.head() # Check that Fact Note was indeed dropped
         census_data.set_index('Fact', inplace=True) #Reset Index to Fact

In [12]: #Make tuple of rows I want to keep for comparison
         census_data_list = census_data.iloc[0],census_data.iloc[29],census_data.iloc[35],censu
         census_data_list = pd.DataFrame (list(census_data_list)) # Convert tuple to dataframe

In [64]: #Output the resulting dataframe to check that desired columns remained
         census_data_list.head()
```

Out[64]:

	Alabama	Alaska	Arizona	\
Population estimates, July 1, 2016, (V2016)	4863300	741894	6931071	
Building permits, 2016	15001	1503	35578	
Bachelor's degree or higher, percent of persons...	0.235	0.28	0.275	
Median household income (in 2015 dollars), 2011...	43623	72515	50255	

	Arkansas	California	\
Population estimates, July 1, 2016, (V2016)	2988248	39250017	
Building permits, 2016	9474	102350	
Bachelor's degree or higher, percent of persons...	0.211	0.314	
Median household income (in 2015 dollars), 2011...	41371	61818	

	Colorado	Connecticut	\

Population estimates, July 1, 2016, (V2016)	5540545	3576452
Building permits, 2016	38974	5504
Bachelor's degree or higher, percent of persons...	0.381	0.376
Median household income (in 2015 dollars), 2011...	60629	70331

	Delaware	Florida	\
Population estimates, July 1, 2016, (V2016)	952065	20612439	
Building permits, 2016	5804	116240	
Bachelor's degree or higher, percent of persons...	0.3	0.273	
Median household income (in 2015 dollars), 2011...	60509	47507	

	Georgia	...	\
Population estimates, July 1, 2016, (V2016)	10310371	...	
Building permits, 2016	51675	...	
Bachelor's degree or higher, percent of persons...	0.288	...	
Median household income (in 2015 dollars), 2011...	49620	...	

	South Dakota	Tennessee	\
Population estimates, July 1, 2016, (V2016)	865454	6651194	
Building permits, 2016	5686	36157	
Bachelor's degree or higher, percent of persons...	0.27	0.249	
Median household income (in 2015 dollars), 2011...	50957	45219	

	Texas	Utah	Vermont	\
Population estimates, July 1, 2016, (V2016)	27862596	3051217	624594	
Building permits, 2016	165853	22662	1771	
Bachelor's degree or higher, percent of persons...	0.276	0.311	0.36	
Median household income (in 2015 dollars), 2011...	53207	60727	55176	

	Virginia	Washington	\
Population estimates, July 1, 2016, (V2016)	8411808	7288000	
Building permits, 2016	31132	44077	
Bachelor's degree or higher, percent of persons...	0.363	0.329	
Median household income (in 2015 dollars), 2011...	65015	61062	

	West Virginia	Wisconsin	\
Population estimates, July 1, 2016, (V2016)	1831102	5778708	
Building permits, 2016	2544	19274	
Bachelor's degree or higher, percent of persons...	0.192	0.278	
Median household income (in 2015 dollars), 2011...	41751	53357	

	Wyoming
Population estimates, July 1, 2016, (V2016)	585501
Building permits, 2016	1727
Bachelor's degree or higher, percent of persons...	0.257
Median household income (in 2015 dollars), 2011...	58840

[4 rows x 50 columns]

```
In [65]: # Transpose dataframe so that we can easily compare dataframes with the gun_data data
         # since state data will now be in the first column
         census_data_list = census_data_list.transpose()
         census_data_list.head()
```

Out[65]:

	Population estimates, July 1, 2016, (V2016)	Building permits, 2016	Bachelor's degree or higher, percent of persons age 25 years+, 2011-2015	Median household income (in 2015 dollars), 2011-2015
Alabama	4863300	15001	0.235	43623
Alaska	741894	1503	0.28	72515
Arizona	6931071	35578	0.275	50255
Arkansas	2988248	9474	0.211	41371
California	39250017	102350	0.314	61818

```
In [20]: #Check shape to make sure all 50 states show up in our dataframe
         census_data_list.shape
```

```
Out[20]: (50, 4)
```

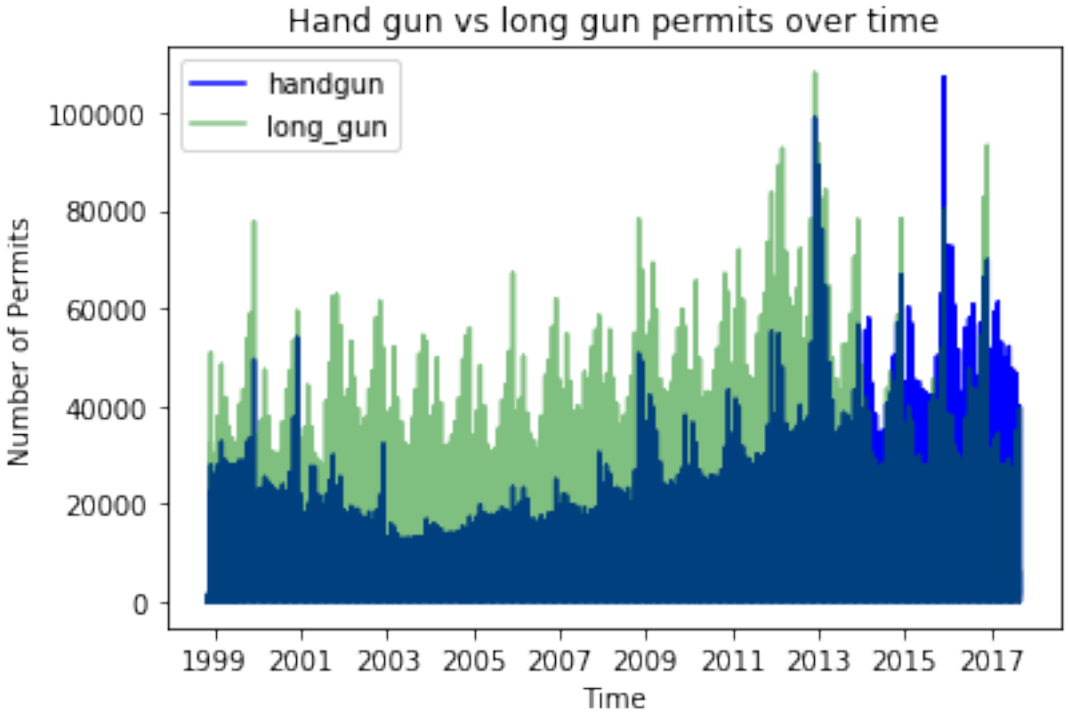
Exploratory Data Analysis

Now that the data is trimmed and cleaned, I move on to the exploration. In the following section, I compute statistics and create visualizations to address the research questions posed in the Introduction section.

1.1.3 What kinds of guns are people applying permits for?

```
In [121]: #I get the specific columns for hand guns and long guns from the gun_data dataframe
          perm_h = gun_data.iloc[:,3] #handguns
          perm_l = gun_data.iloc[:,4] #long_guns
          z_time = gun_data.iloc[:,0] #time variable
```

```
In [124]: #I make a plot of hand_guns over time and long_guns over time on the same graph to c
          first = plt.plot(z_time,perm_h, color = 'blue') #handguns vs permits for each state
          second = plt.plot(z_time,perm_l, color='green', alpha =0.5) #long_guns vs permits fo
          plt.ylabel('Number of Permits')
          plt.title('Hand gun vs long gun permits over time')
          plt.xlabel('Time')
          plt.legend()
          plt.show()
```



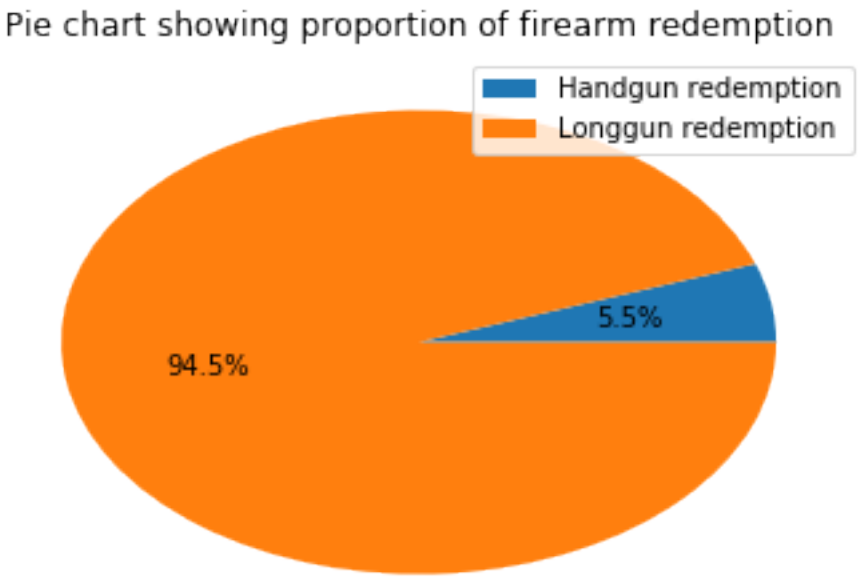
From the mixed plot above, we can see that the permits for both guns appear to be cyclical. This could be partly explained by the seasonality of most of the regions. As an example, most people would not be using guns outside during the winter or outside of hunting season. People would still be purchasing firearms for protection or indoor shooting, so the rate would not fall to zero. On average, it appears that most people in the different states are applying for more permits to own long guns than they do for regular hand guns. The general trend for permit applications appears to be increasing for both types of firearms.

1.1.4 How does redemption data compare between the types of firearms overall?

```
In [24]: #Select hand guns and long guns columns from dataframe
         red_h = gun_data.iloc[:,6] #redemption_handgun
         red_l = gun_data.iloc[:,3] #redemption longgun

In [29]: #PLot a pie chart to show the distribution
         data = [red_h.sum(),red_l.sum()]
```

```
labels = 'Handgun redemption', 'Longgun redemption'
plt.pie(data, autopct='%1.1f%%')
plt.legend(labels, loc=0)
plt.axis = ('equal')
plt.title('Pie chart showing proportion of firearm redemption')
plt.show()
```



More people redeem long guns than they do handguns which is inline with the type of permits they are applying for as we saw in the previous question. There appears to be an overwhelming amount of longgun redemption so we might want to look at the data and see why this number is so disproportional.

1.1.5 How does the percentage of people with Bachelor's degree affect permit applications?

The data from the gun_file has data for multiple years but the census data file only has a snapshot from certain timeperiods, I will take the population estimates from 2016 and compare that with gun data for the average of 2016 data

```
In [30]: #Mean gun data of 2016 to compare with 2016 Census data
         m_2df = pd.to_datetime(gun_data['month']); #month to dataframe
         gun_data['year'] = m_2df.dt.year #make year column
         x = gun_data.loc[gun_data['year'] == 2016]; # Get 2016 data
         gun_summary_df = x.groupby('state').mean(); # Mean of 2016 data by state
         gun_summary_df.head()
```

```
Out[30]:                  permit       handgun      long_gun         other  \
         state
```

```
Alabama     24253.250000  12760.250000  10163.583333    508.666667
Alaska        260.083333   3124.250000   3073.916667    240.750000
Arizona      7314.250000  13898.666667   9082.333333   1093.500000
Arkansas     4621.333333   6687.000000   6843.333333    254.916667
California  86415.083333  46696.250000  46212.500000  17642.250000

            redemption_handgun  redemption_long_gun  year
state
Alabama           1669.666667          1474.750000  2016
Alaska             186.166667           170.500000  2016
Arizona           1381.333333           699.166667  2016
Arkansas          1053.750000          1711.000000  2016
California         562.666667           553.750000  2016
```

In [31]:
```
#Merge the gun_data dataframe with the census_data_list dataframe and output to confi
perm_df = pd.DataFrame(gun_summary_df['permit']);
summary_df = census_data_list.join(perm_df);
summary_df.head()
```

Out[31]:
```
            Population estimates, July 1, 2016,  (V2016)  \
Alabama                                           4863300
Alaska                                             741894
Arizona                                           6931071
Arkansas                                          2988248
California                                       39250017

            Building permits, 2016  \
Alabama                      15001
Alaska                        1503
Arizona                      35578
Arkansas                      9474
California                  102350

            Bachelor's degree or higher, percent of persons age 25 years+, 2011-2015  \
Alabama                                                      0.235
Alaska                                                        0.28
Arizona                                                      0.275
Arkansas                                                     0.211
California                                                   0.314

            Median household income (in 2015 dollars), 2011-2015        permit
Alabama                                                    43623    24253.250000
Alaska                                                     72515      260.083333
Arizona                                                    50255     7314.250000
Arkansas                                                   41371     4621.333333
California                                                 61818    86415.083333
```

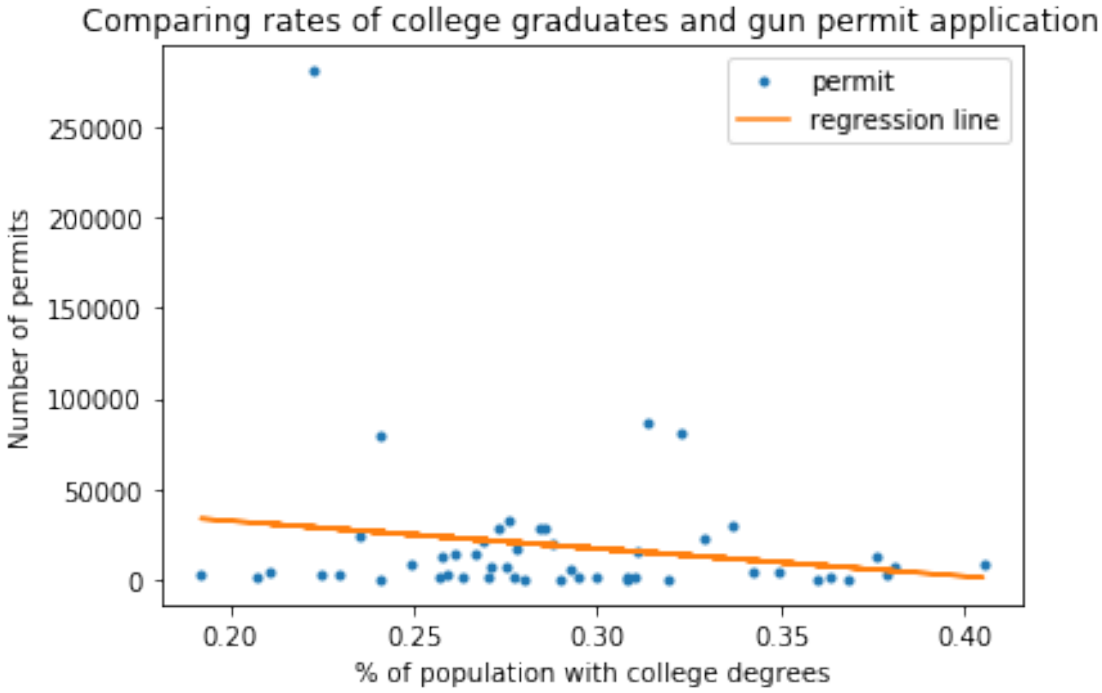
In [34]:
```
#Plot percentage college degrees and above vs permit applications in states
x = summary_df.iloc[:,2] # College Degrees
```

```
x = pd.to_numeric(x) #Convert column from object to numeric so that I can plot it
y = summary_df.iloc[:,4]; #Permit

#Line of best fit with np.ployfit to see relationship
m, b = np.polyfit(x, y, 1)

plt.plot(x, y, '.', label='permit')
plt.plot(x, m*x +b, '-', label='regression line')

plt.ylabel('Number of permits')
plt.xlabel('% of population with college degrees')
plt.legend(loc=1)
plt.title('Comparing rates of college graduates and gun permit application')
plt.show();
```

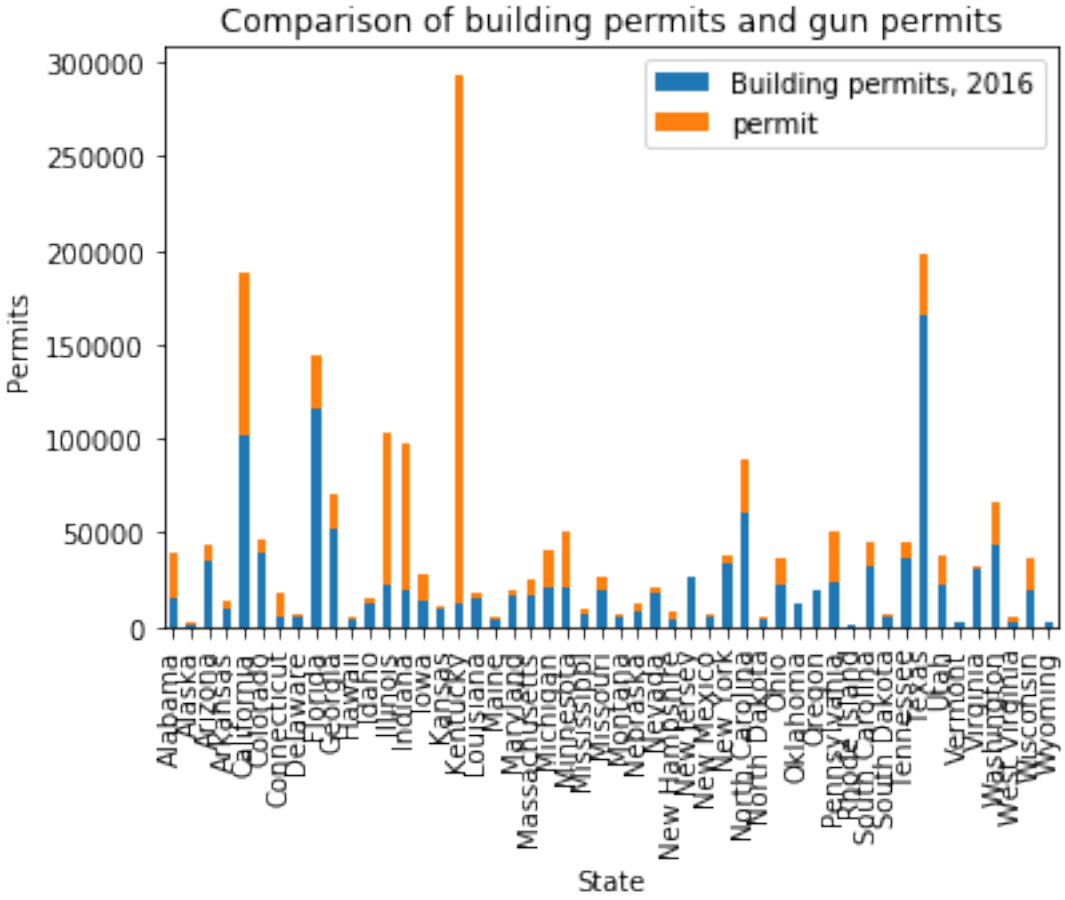


From the plot, it appears that as there is a slight negative correlation between the percentage of people with college degrees and the permit applications in states. States with a higher percentage of college graduates appear to apply for a lower number of permits. It appears that there is an outlier state that has a high number of permit applications even though its proportion of college graduates to that of the general population is low.

1.1.6 To Shoot or to Build: Comparing Business permits vs Firearm permits

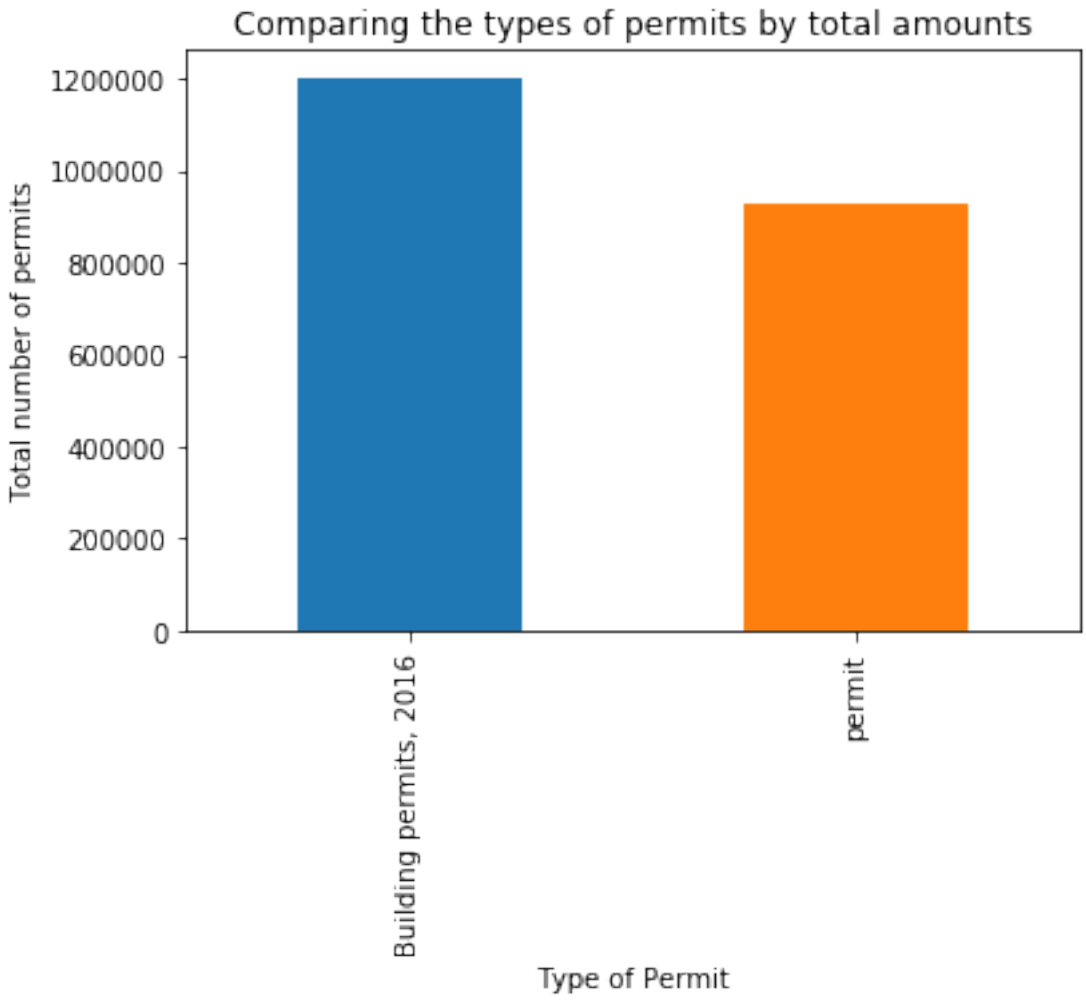
```
In [186]: stack_comp = summary_df[['Building permits, 2016','permit']].plot(kind='bar', stacke
          stack_comp.set_xlabel('State');
```

```
stack_comp.set_ylabel('Permits');
stack_comp.set_title('Comparison of building permits and gun permits');
```



In [191]:
```
combined_bar = summary_df[['Building permits, 2016','permit']].sum().plot(kind='bar'
combined_bar.set_xlabel('Type of Permit');
combined_bar.set_ylabel('Total number of permits');
combined_bar.set_title('Comparing the types of permits by total amounts');
```

Out[191]: Text(0.5,1,'Comparing the types of permits by total amounts')



From the above graphs, it is clear that building permits in most states edge out gun permits but not by a large amount. In fact, it is interesting to note that in a couple of states like Kentucky, the number of gun permits far outnumber those of building permits

1.1.7 Which states have had the highest growth in gun registrations?

For this question, I will look at the average data from 2010 and compare it with that from 2017

```
In [294]: #Relationship between states and gun permits over time
          x = gun_data.groupby(['state'])
          #hand guns vs long guns vs other guns in the states. Here I define the variables
          m_2df = pd.to_datetime(gun_data['month']); #month to dataframe
          gun_data['year'] = m_2df.dt.year #make year column
          x = gun_data.loc[gun_data['year'] == 2012]; # Get 2012 data
          gun_summary_df = x.groupby('state').mean(); # Mean of 2012 data by state
          perm_2012 = pd.DataFrame(gun_summary_df['permit'])
```

```
In [320]: y = gun_data.loc[gun_data['year'] == 2017];
          gun_summary_df = y.groupby('state').mean(); # Mean of 2017 data by state
          perm_2017 = pd.DataFrame(gun_summary_df['permit']);

In [363]: twodf = perm_2017
          twodf = twodf.join(perm_2012)
          twodf.columns = ['2017 Permit Data', '2012 Permit Data']
          twodf['% Growth'] = (twodf['2017 Permit Data'] - twodf['2012 Permit Data']) / ((twod
          twodf.sort_values('% Growth', ascending=False).head()
```

Out[363]:

state	2017 Permit Data	2012 Permit Data	% Growth
Ohio	12165.888889	0.0	12165.888889
Louisiana	2615.111111	0.0	2615.111111
South Dakota	1261.666667	0.0	1261.666667
Virginia	1011.888889	0.0	1011.888889
Maine	721.555556	0.0	721.555556

The top five states that had the highest growth in gun registration were:

```
 <li>Ohio</li>
 <li>Louisiana</li>
 <li>South Dakota</li>
 <li>Virginia</li>
 <li>Maine</li>
</ol>
```

The 2012 permit data from these states is at zero suggesting that there might have been a backlog of processing data that caused this. It could also indicate that there was input error in the data since having no permits in a year does seem like an aberration.

Conclusions

In conclusion, we were able to answer the questions posed at the introduction of this report albeit with some limitations. We found out that people are applying for long guns over handguns although that trend has minimally shifted recently with people seemingly preferring handguns. This could lead to an interesting discussion when it comes to manufacture and selling of the different types of weapons. People redeem more long guns over hand guns which again is congruent with our finding from the first question. It appears there is a slightly negative correlation between number of permits applied for and the percentage of people in those states with a college degree or above.

Finally we can see that from 2017 data, Ohio has had the most growth in number of permit applications in the 5 year span between 2012 and 2017.

I encountered a couple of limitations when doing my analysis. One was that I lacked a robust dataset of population data since the census only takes place every ten years and I was working population estimates from 2016 to make my comparisons between the FBI database and the census database. A second issue I faced had to do with missing data points. When analysing the last question on states with the highest growth in permit applications, I found a lot of states that reported no permit applications. This seems strange and should warrant further investigation from the data source to ensure that integrity of the data we are working with is not being compromised since the lack of reported data in this section could cast doubt on the analysis conducted herein.