Project: NICS Data - A Look at Handgun and Total Checks

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Introduction

For this project I have selected the data from the FBI's NICS database and the US Census for analysis of checks made for firearms purchases. In particular we will look at handgun checks and total checks. I have viewed these two variables mostly over a ten year period so that there are enough years to show any trends. The ten years from 2007 to 2016 shows data that is still current and relevant today in 2018. We will look at the total checks on a per capita basis in 2010 and 2016 since those are the two years for which census data is available.

In [1]:
```
"""Below are the modules that we will import for this project and the
files that we will be reading to retrieve
pertinent data."""

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline

# Note that the file name for the census data has been slightly modifi
ed.
df_fbi = pd.read_excel('NICS_data.xlsx')
df_cen = pd.read_csv('US_census_data.csv')
```

Data Wrangling

General Properties - NICS Data

In [2]:
```
df_fbi.head()
```

Out[2]:

	month	state	permit	permit_recheck	handgun	long_gun	other	multiple	adı
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 [3]:
```
df_fbi.shape
```

Out[3]:
```
(12485, 27)
```

In [4]:
```
df_fbi.columns
```

Out[4]:
```
Index(['month', 'state', 'permit', 'permit_recheck', 'handgun', 'lon
g_gun',
       'other', 'multiple', 'admin', 'prepawn_handgun', 'prepawn_lon
g_gun',
       'prepawn_other', 'redemption_handgun', 'redemption_long_gun',
       'redemption_other', 'returned_handgun', 'returned_long_gun',
       'returned_other', 'rentals_handgun', 'rentals_long_gun',
       'private_sale_handgun', 'private_sale_long_gun', 'private_sal
e_other',
       'return_to_seller_handgun', 'return_to_seller_long_gun',
       'return_to_seller_other', 'totals'],
      dtype='object')
```

In [5]:
```
df_fbi.dtypes
```

Out[5]:
```
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 [6]:
```
# Are there any null values in the data?
df_fbi.isnull().sum()
```

Out[6]:
```
month                            0
state                            0
permit                          24
permit_recheck               11385
handgun                         20
long_gun                        19
other                         6985
multiple                         0
admin                           23
prepawn_handgun               1943
prepawn_long_gun              1945
prepawn_other                 7370
redemption_handgun            1940
redemption_long_gun           1941
redemption_other              7370
returned_handgun             10285
returned_long_gun            10340
returned_other               10670
rentals_handgun              11495
rentals_long_gun             11660
private_sale_handgun          9735
private_sale_long_gun         9735
private_sale_other            9735
return_to_seller_handgun     10010
return_to_seller_long_gun     9735
return_to_seller_other       10230
totals                           0
dtype: int64
```

In [7]:
```
# How many states are included in this data?
df_fbi['state'].nunique()
```

Out[7]:
```
55
```

In [8]:
```
# Why are there more than 50 states?
# Ans: We can see that the data includes Guam, Puerto Rico, Wash. DC,
the Virgin Islands and the Mariana Islands.
states_fbi = df_fbi['state'].unique()
print(states_fbi)
```

```
['Alabama' 'Alaska' 'Arizona' 'Arkansas' 'California' 'Colorado'
 'Connecticut' 'Delaware' 'District of Columbia' 'Florida' 'Georgia'
 'Guam' 'Hawaii' 'Idaho' 'Illinois' 'Indiana' 'Iowa' 'Kansas' 'Kentu
cky'
 'Louisiana' 'Maine' 'Mariana Islands' 'Maryland' 'Massachusetts'
 'Michigan' 'Minnesota' 'Mississippi' 'Missouri' 'Montana' 'Nebraska
'
 'Nevada' 'New Hampshire' 'New Jersey' 'New Mexico' 'New York'
 'North Carolina' 'North Dakota' 'Ohio' 'Oklahoma' 'Oregon' 'Pennsyl
vania'
 'Puerto Rico' 'Rhode Island' 'South Carolina' 'South Dakota' 'Tenne
ssee'
 'Texas' 'Utah' 'Vermont' 'Virgin Islands' 'Virginia' 'Washington'
 'West Virginia' 'Wisconsin' 'Wyoming']
```

In [9]:
```
# Let's make sure that the dates are in a workable format and also see
the earliest and most recent months.
df_fbi['month'].min(), df_fbi['month'].max()
```

Out[9]:
```
('1998-11', '2017-09')
```

In [10]:
```
df_fbi.shape
```

Out[10]:
```
(12485, 27)
```

In [11]:
```
df_fbi.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
```

Cleaning - NICS Data

Now that we have an idea of what is in the data let's clean a few items up such as the states that are included and the null values.

In [12]:
```
# Let's check what values we need to remove from the 'state' field.

fifty_states = df_fbi['state'].unique().tolist()
states_to_remove = ['District of Columbia', 'Guam', 'Mariana Islands',
'Puerto Rico', 'Virgin Islands']
```

In [13]:
```
fifty_states = [i for i in fifty_states if i not in states_to_remove]
```

In [14]:
```
df_fbi = df_fbi[df_fbi['state'].isin(fifty_states)]
```

In [15]:
```
df_fbi['permit'].fillna(0, inplace=True)

# Let's check to make sure that there are no null values in the 'permi
t' column.

df_fbi['permit'].isnull().value_counts()
```

Out[15]:
```
False    11350
Name: permit, dtype: int64
```

In [16]:
```
# Now let's include the year as a separate column so that we can view
data on an annual basis.
year = df_fbi['month'].str[0:4]
```

In [17]:
```
# This will add a 'year' column on the right side of our data frame.
df_fbi = df_fbi.assign(year=year)
```

In [18]:
```
Alabama = df_fbi.state == 'Alabama'
Alaska = df_fbi.state == 'Alaska'
Washington = df_fbi.state == 'Washington'
```

General Properties - Census Data

Next let's now do some work on reviewing, cleaning and organizing the census dataset.

In [19]:
```
df_cen.head(3)
```

Out[19]:

	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 rows × 52 columns

In [20]:
```
# If we transpose the data set then it will be easier to read and the state populations for 2010
    # and 2016 will better line up with the NICS data that we have.

df_cen = df_cen.transpose()
```

In [21]:
```
df_cen.head()
```

Out[21]:

	0	1	2	3	4	5	6	
Fact	Population estimates, July 1, 2016, (V2016)	Population estimates base, April 1, 2010, (V2...	Population, percent change - April 1, 2010 (es...	Population, Census, April 1, 2010	Persons under 5 years, percent, July 1, 2016, ...	Persons under 5 years, percent, April 1, 2010	Persons under 18 years, percent, July 1, 2016,...	Per und 18 yea per Apr 201
Fact Note	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Nal
Alabama	4,863,300	4,780,131	1.70%	4,779,736	6.00%	6.40%	22.60%	23.
Alaska	741,894	710,249	4.50%	710,231	7.30%	7.60%	25.20%	26.
Arizona	6,931,071	6,392,301	8.40%	6,392,017	6.30%	7.10%	23.50%	25.

5 rows × 85 columns

In [22]:
```
# It will help if we rename the two most critical columns.  Then we ca
n
    # create a dataframe that contains only those two columns.

df_cen.rename(columns={0: 'pop_est_2016', 1: 'pop_est_2010', 6: 'perc_
under_18_2016', 7:
                       'perc_under_18_2010'}, inplace=True)
```

In [23]:
```
# Let's check to see if the values are correct and to see the data typ
e.
alabama_pop_2016 = df_cen['pop_est_2016'].iloc[2]
print('value:', alabama_pop_2016, '\n', 'data type:', type(alabama_pop
_2016))
```

```
value: 4,863,300
 data type: <class 'str'>
```

In [24]:
```
df_cen.shape
```

Out[24]:
```
(52, 85)
```

Cleaning - Census Data

In [25]:
```
# There are a couple of rows that we will not be using.

df_cen.drop(['Fact', 'Fact Note'], axis=0, inplace=True)
```

In [26]:
```
df_cen['pop_est_2010'] = df_cen['pop_est_2010'].str.replace(',', '')
df_cen['pop_est_2016'] = df_cen['pop_est_2016'].str.replace(',', '')
```

In [27]:
```
df_cen['pop_est_2010'] = df_cen['pop_est_2010'].astype(int)
df_cen['pop_est_2016'] = df_cen['pop_est_2016'].astype(int)
```

In [28]:
```
df_cen['perc_under_18_2016'] = df_cen['perc_under_18_2016'].str.rstrip
('%')
df_cen['perc_under_18_2010'] = df_cen['perc_under_18_2010'].str.rstrip
('%')
```

In [29]:
```
df_cen['perc_under_18_2016'] = df_cen['perc_under_18_2016'].astype(flo
at)
df_cen['perc_under_18_2010'] = df_cen['perc_under_18_2010'].astype(flo
at)
```

In [30]:
```
"""Some of the population percentage values were in a percentage forma
t while others were in a decimal format.  The
function below will make sure that they are all in a decimal format be
tween 0.0 and 1.0"""

def reduction(a):
    if a > 1:
        return a/100
    else:
        return a

df_cen['perc_under_18_2016'] = df_cen['perc_under_18_2016'].apply(redu
ction)
df_cen['perc_under_18_2010'] = df_cen['perc_under_18_2010'].apply(redu
ction)
```

In [31]:
```
# Let's check for null values in the percentage columns.  There should
not be any.
print(df_cen['perc_under_18_2016'].isnull().value_counts())
print(df_cen['perc_under_18_2010'].isnull().value_counts())
```

```
False    50
Name: perc_under_18_2016, dtype: int64
False    50
Name: perc_under_18_2010, dtype: int64
```

In [32]:
```
# Let's make sure that the data types for the state populations were u
pdated properly.
df_cen.dtypes.iloc[0:10]
```

Out[32]:
```
pop_est_2016            int64
pop_est_2010            int64
2                      object
3                      object
4                      object
5                      object
perc_under_18_2016    float64
perc_under_18_2010    float64
8                      object
9                      object
dtype: object
```

In [33]:
```
df_cen['adult_perc_2016'] = 1 - df_cen['perc_under_18_2016']
df_cen['adult_perc_2010'] = 1 - df_cen['perc_under_18_2010']

# We now need to multiply the population colums with the adult percent
age columns to view the adult population.
df_cen['adult_pop_2016'] = df_cen['pop_est_2016'] * df_cen['adult_perc
_2016']
df_cen['adult_pop_2010'] = df_cen['pop_est_2010'] * df_cen['adult_perc
_2010']
```

In [34]:
```
df_cen.head()
```

Out[34]:

	pop_est_2016	pop_est_2010	2	3	4	5	perc_under
Alabama	4863300	4780131	1.70%	4,779,736	6.00%	6.40%	0.226
Alaska	741894	710249	4.50%	710,231	7.30%	7.60%	0.252
Arizona	6931071	6392301	8.40%	6,392,017	6.30%	7.10%	0.235
Arkansas	2988248	2916025	2.50%	2,915,918	6.40%	6.80%	0.236
California	39250017	37254522	5.40%	37,253,956	6.30%	6.80%	0.232

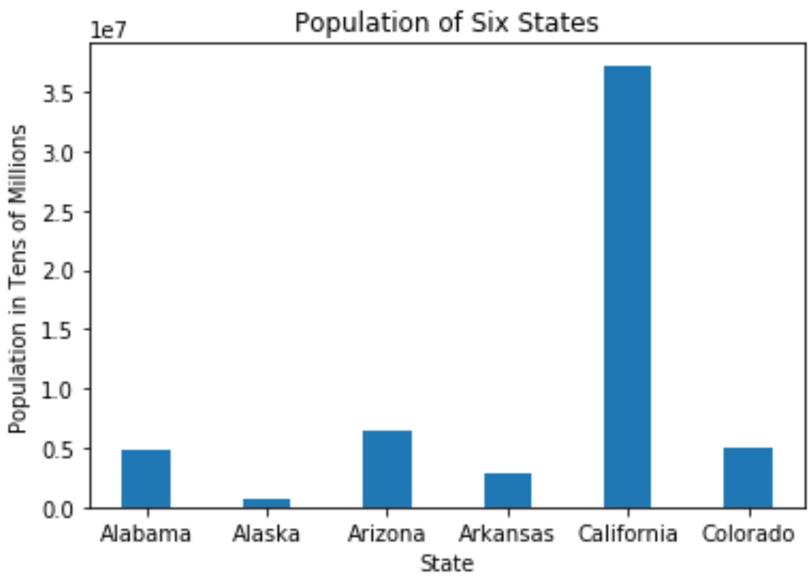
5 rows × 89 columns

In [35]:
```
"""Let's make sure that the states and their populations are appearing as they should.  We'll also set up an
index of the first six states on the list to make a graph next."""

state_pop_2010 = list(df_cen['pop_est_2010'].iloc[0:6])
print(state_pop_2010, '\n')

states_cen = df_cen.index
first_6_states = df_cen.index[0:6]
print(first_6_states, '\n')

max_pop = df_cen['pop_est_2010'].max()
print('largest state pop:', max_pop)

min_pop = df_cen['pop_est_2010'].min()
print('smallest state pop:', min_pop)
```

```
[4780131, 710249, 6392301, 2916025, 37254522, 5029324]

Index(['Alabama', 'Alaska', 'Arizona', 'Arkansas', 'California', 'Co
lorado'], dtype='object')

largest state pop: 37254522
smallest state pop: 563767
```

In [36]:
```
# Let's also setup a bar graph with a few state populations as a test.

x = [2, 4, 6, 8, 10, 12]

plt.bar(x, state_pop_2010, align='center', tick_label=first_6_states)
plt.title('Population of Six States')
plt.xlabel('State')
plt.ylabel('Population in Tens of Millions')
```

Out[36]:
```
Text(0, 0.5, 'Population in Tens of Millions')
```



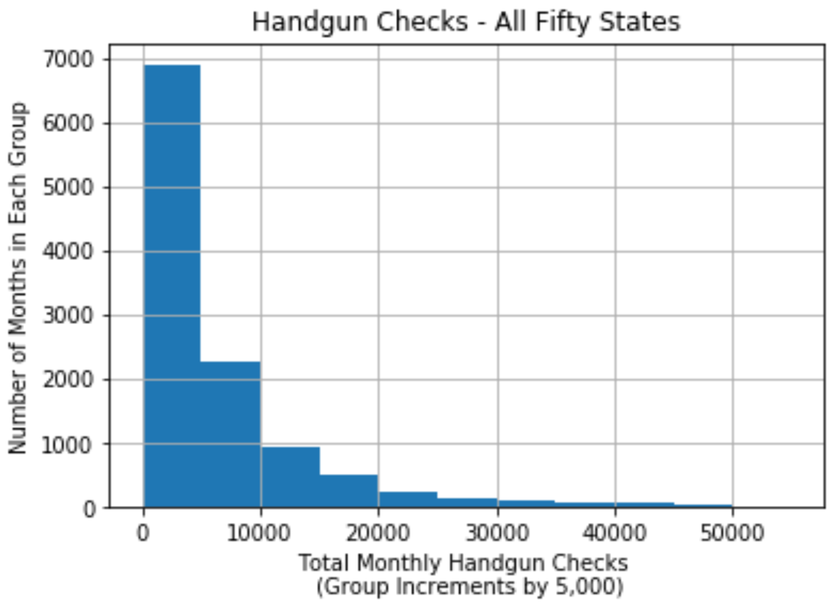
Exploratory Data Analysis

Research Question 1: Which states showed the highest growth in handgun checks over a ten year period? Can we suggest any reasons for these increases?

Before we dive in, let's take a look at a histogram of the monthly handgun check data for all states and also for the first two states on the list. That will give us a general idea of the number of monthly checks.

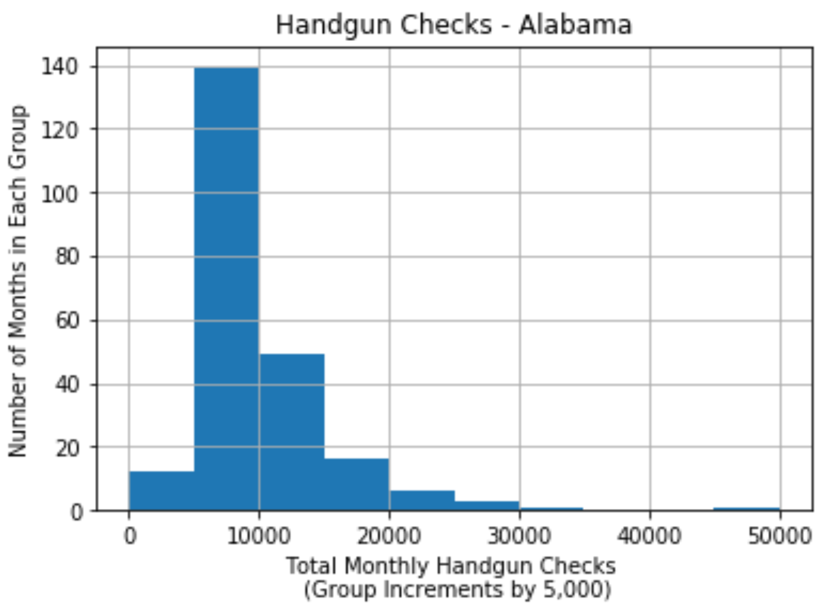
In [37]:
```
bins = [0, 5000, 10000, 15000, 20000, 25000, 30000, 35000, 40000, 4500
0, 50000, 55000]
df_fbi.handgun.hist(bins=bins)
plt.title('Handgun Checks - All Fifty States')
plt.xlabel('Total Monthly Handgun Checks \n (Group Increments by 5,000
)')
plt.ylabel('Number of Months in Each Group')
```

Out[37]:
```
Text(0, 0.5, 'Number of Months in Each Group')
```



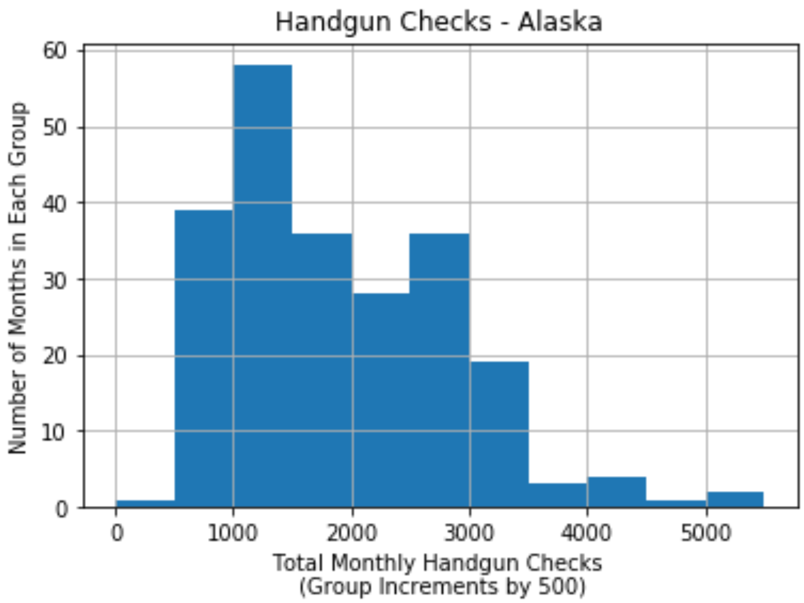
In [38]:
```
bins = [0, 5000, 10000, 15000, 20000, 25000, 30000, 35000, 40000, 4500
0, 50000]
df_fbi.handgun[Alabama].hist(bins=bins)
plt.title('Handgun Checks - Alabama')
plt.xlabel('Total Monthly Handgun Checks \n (Group Increments by 5,000
)')
plt.ylabel('Number of Months in Each Group')
```

Out[38]:
```
Text(0, 0.5, 'Number of Months in Each Group')
```



In [40]:
```
bins = [0, 500, 1000, 1500, 2000, 2500, 3000, 3500, 4000, 4500, 5000,
5500]
df_fbi.handgun[Alaska].hist(bins=bins)
plt.title('Handgun Checks - Alaska')
plt.xlabel('Total Monthly Handgun Checks \n (Group Increments by 500)'
)
plt.ylabel('Number of Months in Each Group')
```

Out[40]:
```
Text(0, 0.5, 'Number of Months in Each Group')
```



There were usually fewer than 10,000 checks per month in each state but a in some states there were months when the total far exceeded that number. A look at the handgun checks for Alabama shows that most monhts had between 5,000 and 15,000 NICS approvals. A look at the handgun checks for Alaska shows that most monhts had between 500 and 3,500 NICS approvals.

In [41]:
```
# Next let's look at the states with the largest increase in permits n
ominal terms for a given year or in total.

NICS_totals = df_fbi.groupby('state')['totals'].sum()
handgun_totals = df_fbi.groupby('state')['handgun'].sum()
handgun_percentage = ((handgun_totals / NICS_totals).round(3))*100
```

In [42]:
```
# What ten states have seen largest percentage increase in approved ba
ckground checks for handgun purchases
#    from the year 2007 to 2016?

ten_years = [2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 201
6]

handgun_per_yr = df_fbi.groupby(['year', 'state'])['handgun'].sum()
handgun_2007 = handgun_per_yr['2007']
handgun_2008 = handgun_per_yr['2008']
handgun_2009 = handgun_per_yr['2009']
handgun_2010 = handgun_per_yr['2010']
handgun_2011 = handgun_per_yr['2011']
handgun_2012 = handgun_per_yr['2012']
handgun_2013 = handgun_per_yr['2013']
handgun_2014 = handgun_per_yr['2014']
handgun_2015 = handgun_per_yr['2015']
handgun_2016 = handgun_per_yr['2016']
handgun_increase = handgun_2016 - handgun_2007
```

In [43]:
```
handgun_perc_incr = ((handgun_increase / handgun_2007)*100).round(2)

# It looks like we are going to have to strip out PA due to the way th
at they classify handguns and long guns.
#    Specifically, there appears to have been a major classification c
hange in late 2013 or early 2014.

# In the data cleaning phase we stripped out non-US states since their
relatively low number of permits makes
#    it so that small change in absolute number of permits has a major
impact on percentage changes.

# Next we need to work on a top 10 or 12 list.
```

In [44]:
```
top_11_handgun = handgun_perc_incr.nlargest(11)
top_10_handgun = top_11_handgun.drop('Pennsylvania')
```

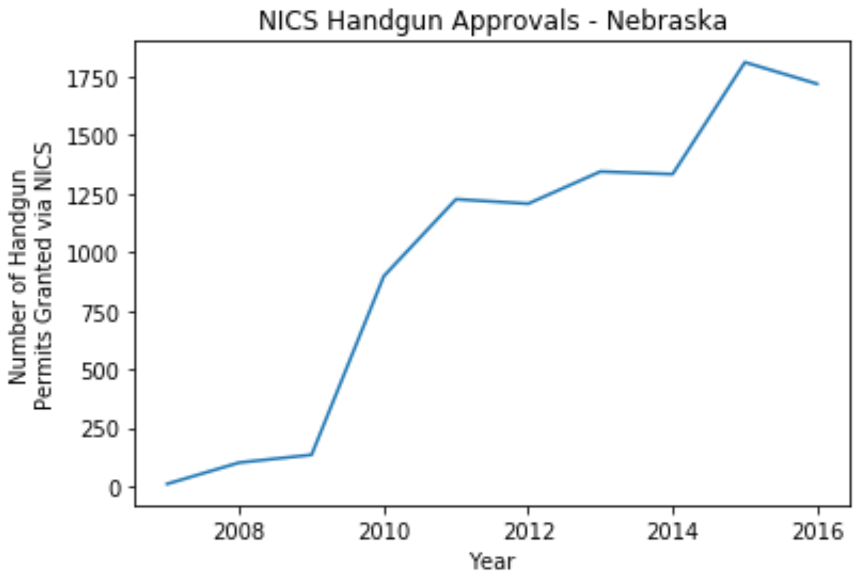
In [45]:
```
print(top_10_handgun)
```

```
state
Nebraska          15509.09
Iowa               1107.79
Michigan            569.72
North Carolina      535.82
Illinois            447.44
Wisconsin           327.78
New Jersey          325.62
Connecticut         308.04
Delaware            305.94
Indiana             273.17
Name: handgun, dtype: float64
```

In [46]:
```
"""The following function will make a list for any given state to show
the number of NICS handgun permits each year
over a ten-year period."""

def state_handguns(a):
    b = []
    i = 2007
    while i < 2017:
        i = str(i)
        b.append(handgun_per_yr[i][a])
        i = int(i)
        i += 1
    return(b)

NE = state_handguns('Nebraska')
IA = state_handguns('Iowa')
MI = state_handguns(top_10_handgun.index[2])
NC = state_handguns(top_10_handgun.index[3])
IL = state_handguns(top_10_handgun.index[4])
WI = state_handguns(top_10_handgun.index[5])
NJ = state_handguns(top_10_handgun.index[6])
CT = state_handguns(top_10_handgun.index[7])
DE = state_handguns(top_10_handgun.index[8])
IN = state_handguns(top_10_handgun.index[9])
```

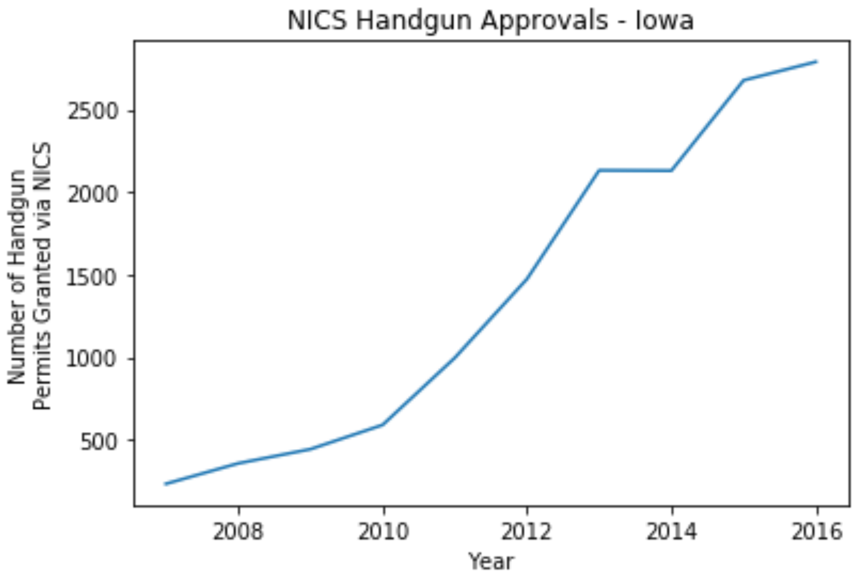
In [47]:
```
"""The information above looks really interesting.  Let's graph some o
f these states to see when the
increases occurred.  In cases where the scaling is similar, states wil
l be graphed togeher rather than separately."""

plt.plot(ten_years, NE, label='Nebraska')
plt.title('NICS Handgun Approvals - Nebraska')
plt.xlabel('Year')
plt.ylabel('Number of Handgun\n' 'Permits Granted via NICS')
```

Out[47]: `Text(0, 0.5, 'Number of Handgun\nPermits Granted via NICS')`



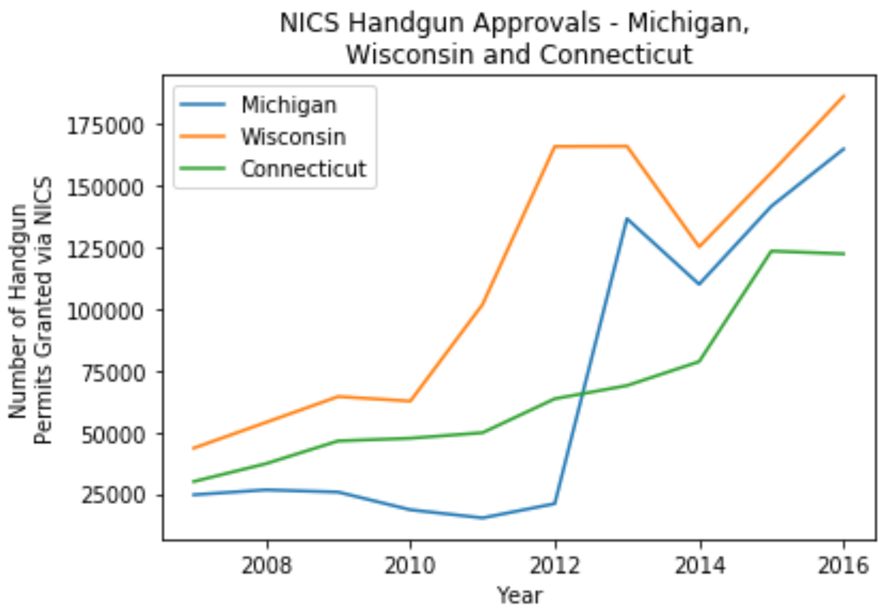
In [48]:
```
plt.plot(ten_years, IA, label='Iowa')
plt.title('NICS Handgun Approvals - Iowa')
plt.xlabel('Year')
plt.ylabel('Number of Handgun\n' 'Permits Granted via NICS')
```

Out[48]:
```
Text(0, 0.5, 'Number of Handgun\nPermits Granted via NICS')
```



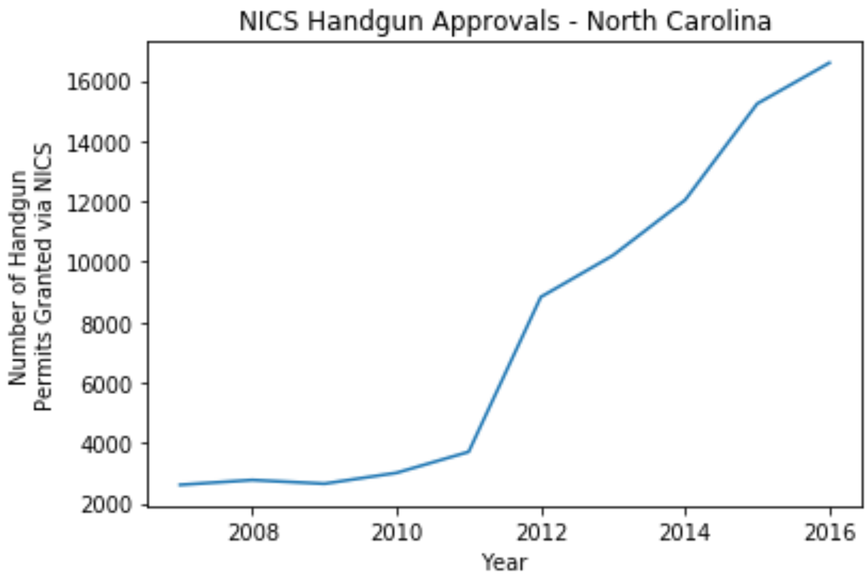
In [49]:
```
plt.plot(ten_years, MI, label='Michigan')
plt.plot(ten_years, WI, label='Wisconsin')
plt.plot(ten_years, CT, label='Connecticut')
plt.title('NICS Handgun Approvals - Michigan, \n' 'Wisconsin and Conne
cticut')
plt.xlabel('Year')
plt.ylabel('Number of Handgun\n' 'Permits Granted via NICS')
plt.legend()
```

Out[49]: <matplotlib.legend.Legend at 0x11da23748>



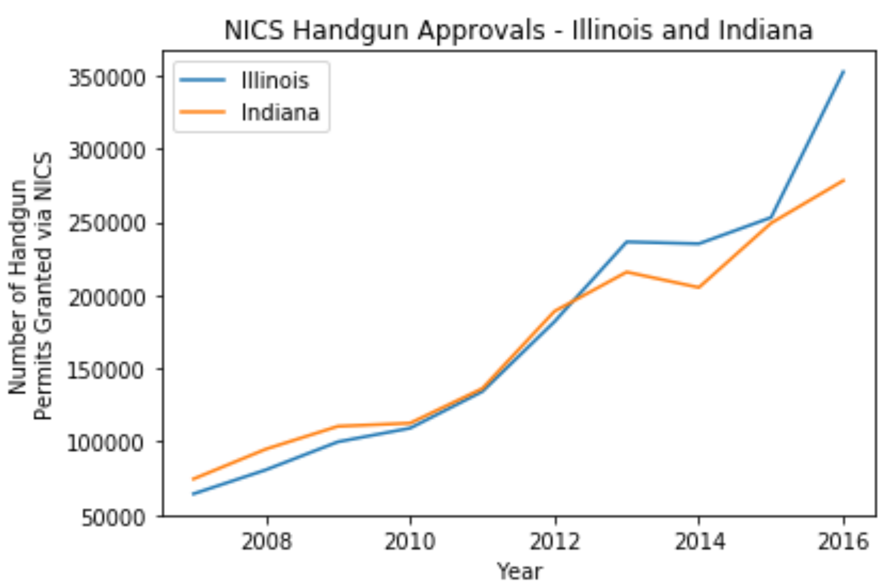
In [50]:
```
plt.plot(ten_years, NC)
plt.title('NICS Handgun Approvals - North Carolina')
plt.xlabel('Year')
plt.ylabel('Number of Handgun\n' 'Permits Granted via NICS')
```

Out[50]:
```
Text(0, 0.5, 'Number of Handgun\nPermits Granted via NICS')
```



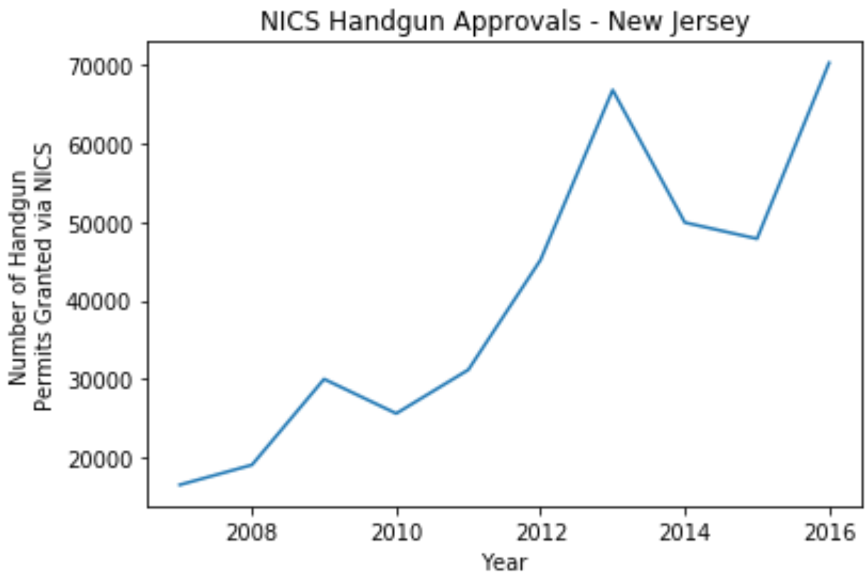
In [51]:
```
plt.plot(ten_years, IL, label='Illinois')
plt.plot(ten_years, IN, label='Indiana')
plt.title('NICS Handgun Approvals - Illinois and Indiana')
plt.xlabel('Year')
plt.ylabel('Number of Handgun\n' 'Permits Granted via NICS')
plt.legend()
```

Out[51]:
```
<matplotlib.legend.Legend at 0x11d747198>
```



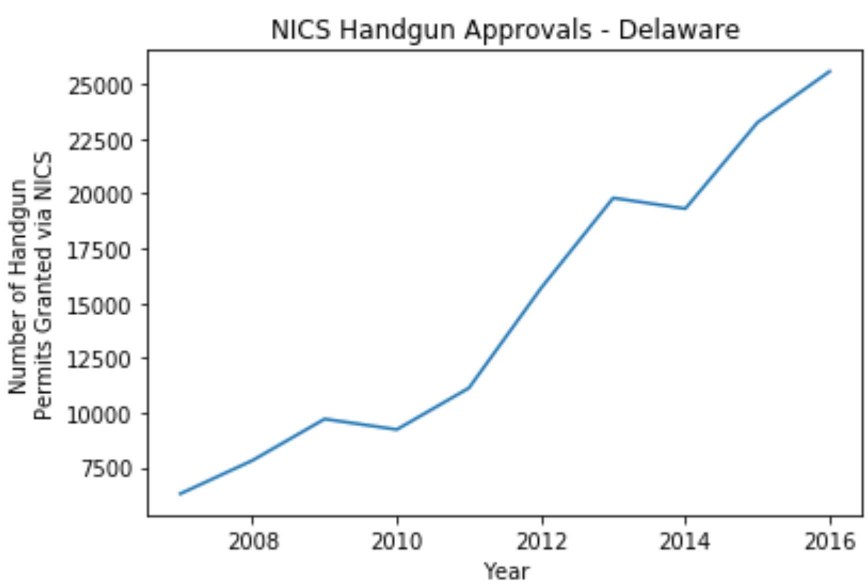
In [52]:
```
plt.plot(ten_years, NJ)
plt.title('NICS Handgun Approvals - New Jersey')
plt.xlabel('Year')
plt.ylabel('Number of Handgun\n' 'Permits Granted via NICS')
```

Out[52]:
```
Text(0, 0.5, 'Number of Handgun\nPermits Granted via NICS')
```



In [53]:
```
plt.plot(ten_years, DE)
plt.title('NICS Handgun Approvals - Delaware')
plt.xlabel('Year')
plt.ylabel('Number of Handgun\n' 'Permits Granted via NICS')
```

Out[53]:
```
Text(0, 0.5, 'Number of Handgun\nPermits Granted via NICS')
```



Observation: In the graphs above we can see that in certain cases, such as Michigan and Wisconsin, that the jump in NICS handgun checks in the 2010 and 2012 periods, respectively, was more likely due to changes in firearm classification than in actual increases in handgun checks. In other states where there is a more steady increase over the ten-year period it is more plausible that there was indeed a major increase in phone calls to the NICS to approve handguns purchases.

Research Question 2: What trends can we observe in terms of total NICS checks and per capita approvals? Are there particular states that show large increases in checks on a per capita basis?

Now that we have analyzed handgun permits we can see that those figures were impacted by how permits were classified. It would be helpful to view per capita figures for all NICS checks, the 'totals' column, in order to get a better sense of what the grow trend was. We will look at 2010 and 2016 since those are the two years for which we have population data. We will look at the totals on an absolute basis and also on a per capita basis.

In [54]:
```
adult_pop_2016 = df_cen['adult_pop_2016']
adult_pop_2010 = df_cen['adult_pop_2010']
populations = pd.concat([adult_pop_2016, adult_pop_2010], axis=1)
```

In [55]:
```
print(populations.shape)
print(populations.dtypes)
```

```
(50, 2)
adult_pop_2016    float64
adult_pop_2010    float64
dtype: object
```

In [56]:
```
df_fbi['totals'].shape
```

Out[56]:
```
(11350,)
```

In [57]:
```
total_2007 = df_fbi['year'] == '2007'
total_2008 = df_fbi['year'] == '2008'
total_2009 = df_fbi['year'] == '2009'
total_2010 = df_fbi['year'] == '2010'
total_2011 = df_fbi['year'] == '2011'
total_2012 = df_fbi['year'] == '2012'
total_2013 = df_fbi['year'] == '2013'
total_2014 = df_fbi['year'] == '2014'
total_2015 = df_fbi['year'] == '2015'
total_2016 = df_fbi['year'] == '2016'
```

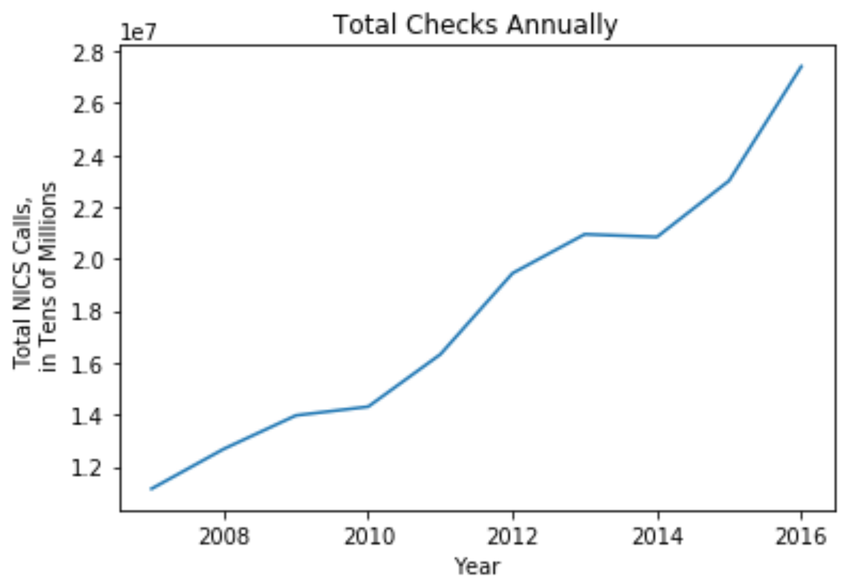
In [58]:
```
totals_2007_to_2016 = [df_fbi.totals[total_2007].sum(), df_fbi.totals[
total_2008].sum(), \
                        df_fbi.totals[total_2009].sum(), df_fbi.totals
[total_2010].sum(), \
                        df_fbi.totals[total_2011].sum(), df_fbi.totals
[total_2012].sum(), \
                        df_fbi.totals[total_2013].sum(), df_fbi.totals
[total_2014].sum(), \
                        df_fbi.totals[total_2015].sum(), df_fbi.totals
[total_2016].sum()]
```

In [59]:
```
print(totals_2007_to_2016)
```

```
[11151998, 12684240, 13974323, 14309926, 16323039, 19446504, 2094676
1, 20840268, 23006228, 27405549]
```

In [60]:
```
plt.plot(ten_years, totals_2007_to_2016)
plt.title('Total Checks Annually')
plt.xlabel('Year')
plt.ylabel('Total NICS Calls, \n in Tens of Millions')
```

Out[60]:
```
Text(0, 0.5, 'Total NICS Calls, \n in Tens of Millions')
```



In [61]:
```
annual_check_incr = ((df_fbi.totals[total_2016].sum() / df_fbi.totals[
total_2007].sum())**(1/9) - 1)*100
```

In [62]:
```
print('The line on the chart looks quite steep but it is important to
remember that this represents an annualized \
increase of approximately', round(annual_check_incr, 1), '%.')
```

```
The line on the chart looks quite steep but it is important to remem
ber that this represents an annualized increase of approximately 10.
5 %.
```

Next let's look at permits per capita in 4 states that have a high population and substantially different regulations pertaining to gun laws. We will look at CA, FL, NY and TX. I would like to know if the trends are similar or substantially different. We will have to graph them on separate graphs since the scales are different.

In [63]:
```
"""This fuction will allow us to show the total number of checks made
in a given state over a ten year period."""

check_per_yr = df_fbi.groupby(['year', 'state'])['totals'].sum()

def state_totals(a):
    c = []
    i = 2007
    while i < 2017:
        i = str(i)
        c.append(check_per_yr[i][a])
        i = int(i)
        i += 1
    return c
```

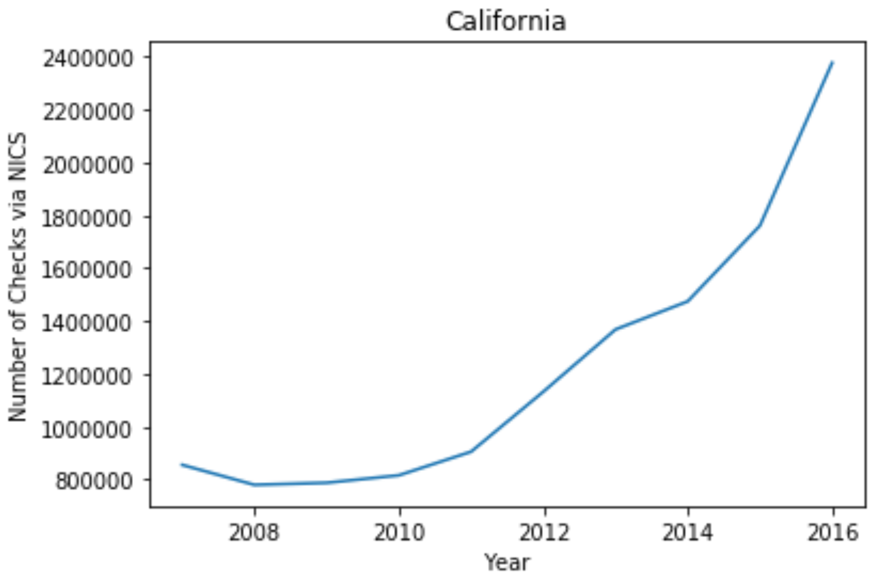
In [64]:
```
CA_totals = state_totals('California')
FL_totals = state_totals('Florida')
NY_totals = state_totals('New York')
TX_totals = state_totals('Texas')
```

In [65]:
```
# I would like to make sure that the lists appear as they should for g
raphing.
print(CA_totals, '\n', FL_totals, '\n', NY_totals, '\n', TX_totals)
```

```
[855943, 780398, 788164, 816399, 905701, 1132603, 1368295, 1474616,
1761079, 2377167]
 [426180, 503672, 556540, 559347, 643229, 834319, 1073859, 1034546,
1147082, 1435340]
 [212174, 221920, 241165, 241495, 271837, 338619, 353064, 365427, 34
6048, 404772]
 [783596, 944568, 1014015, 968071, 1155387, 1436132, 1633278, 146599
2, 1574266, 1721726]
```

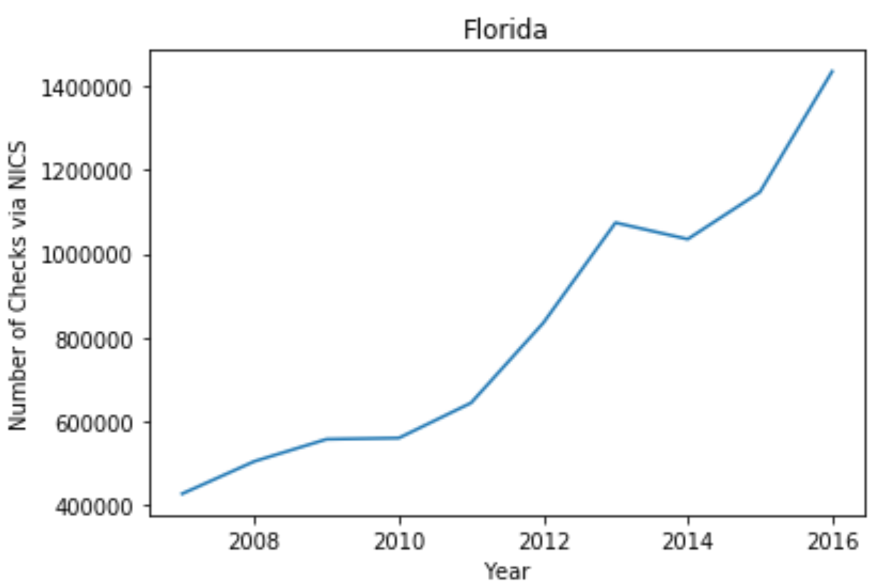
In [66]:
```
plt.plot(ten_years, CA_totals)
plt.title('California')
plt.xlabel('Year')
plt.ylabel('Number of Checks via NICS')
```

Out[66]: Text(0, 0.5, 'Number of Checks via NICS')



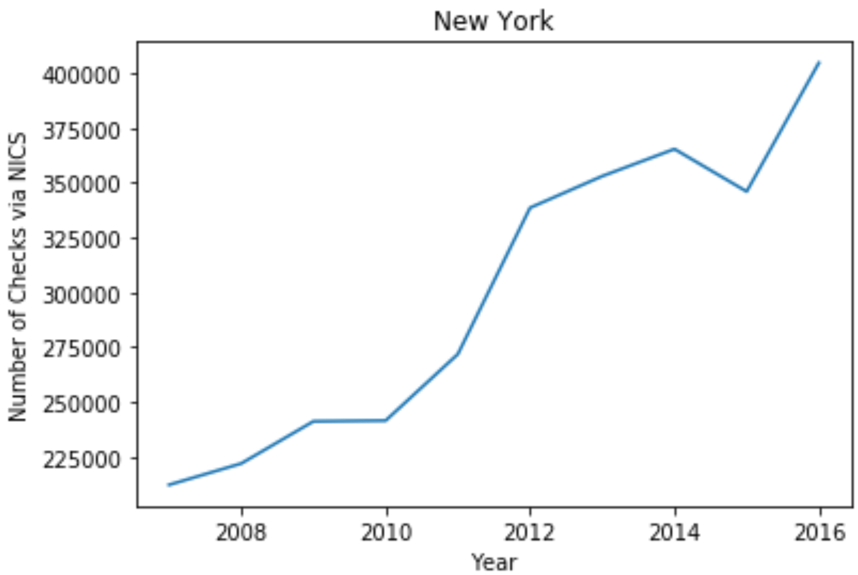
In [67]:
```
plt.plot(ten_years, FL_totals)
plt.title('Florida')
plt.xlabel('Year')
plt.ylabel('Number of Checks via NICS')
```

Out[67]: Text(0, 0.5, 'Number of Checks via NICS')



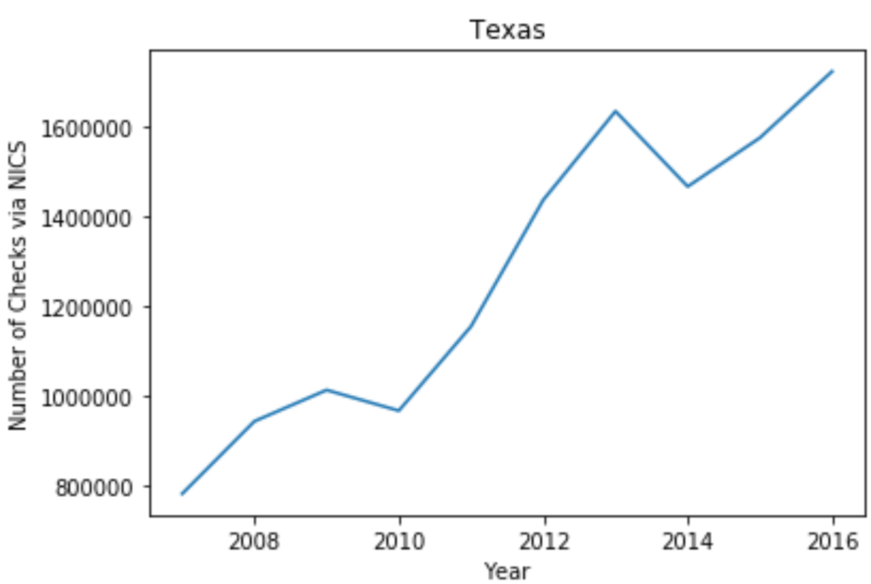
In [68]:
```
plt.plot(ten_years, NY_totals)
plt.title('New York')
plt.xlabel('Year')
plt.ylabel('Number of Checks via NICS')
```

Out[68]: Text(0, 0.5, 'Number of Checks via NICS')



In [69]:
```
plt.plot(ten_years, TX_totals)
plt.title('Texas')
plt.xlabel('Year')
plt.ylabel('Number of Checks via NICS')
```

Out[69]: Text(0, 0.5, 'Number of Checks via NICS')



California shows a rather marked increase beginning around 2011 but generally speaking the four states shown above show increases that are similar to the national trend for total checks via NICS.

As a final step we will take a look at the per capita figures. This will give us an idea of which states show the hightest number of total checks per capita and we can use the 2010 and 2016 census data to get an idea of the changes between those two years.

In [70]:
```
total_checks_2010 = check_per_yr['2010']
total_checks_2016 = check_per_yr['2016']
```

In [71]:
```
checks_2010_2016 = pd.concat([populations, total_checks_2016], axis=1)
```

In [72]:
```
checks_2010_2016.shape
```

Out[72]: (50, 3)

In [73]:
```
checks_2010_2016.rename(columns={'totals': '2016_total_checks'}, inpla
ce=True)
```

In [74]:
```
checks_2010_2016 = pd.concat([checks_2010_2016, total_checks_2010], ax
is=1)
```

In [75]:
```
checks_2010_2016.rename(columns={'totals': '2010_total_checks'}, inpla
ce=True)
```

In [76]:
```
checks_2010_2016['per_capita_2016'] = checks_2010_2016['2016_total_che
cks'] / checks_2010_2016['adult_pop_2016']
checks_2010_2016['per_capita_2010'] = checks_2010_2016['2010_total_che
cks'] / checks_2010_2016['adult_pop_2010']
checks_2010_2016['per_capita_change'] = checks_2010_2016['per_capita_2
016'] - checks_2010_2016['per_capita_2010']
```

In [77]:
```
checks_2010_2016.head()
```

Out[77]:

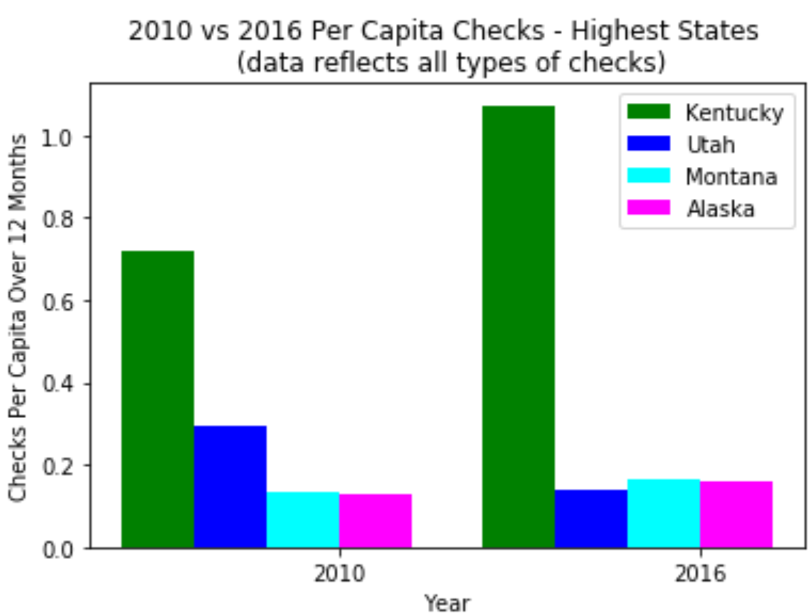
	adult_pop_2016	adult_pop_2010	2016_total_checks	2010_total_checks	pe
state					
Alabama	3.764194e+06	3.647240e+06	616947	308607	0.1
Alaska	5.549367e+05	5.227433e+05	87647	65909	0.1
Arizona	5.302269e+06	4.762264e+06	416279	206050	0.0
Arkansas	2.283021e+06	2.204515e+06	266014	191448	0.1
California	3.014401e+07	2.794089e+07	2377167	816399	0.0

In [78]:
```
# Let's graph the per capita increases for the 4 states that had the f
ewest checks per capita
#    and for the 4 states that had the most checks per capita in 2010.

print(checks_2010_2016['per_capita_2010'].nlargest(4))
print(checks_2010_2016['per_capita_2010'].nsmallest(4))
```

```
state
Kentucky    0.719575
Utah        0.292159
Montana     0.132011
Alaska      0.126083
Name: per_capita_2010, dtype: float64
state
New Jersey      0.007512
Hawaii          0.009965
New York        0.016039
Rhode Island    0.017902
Name: per_capita_2010, dtype: float64
```

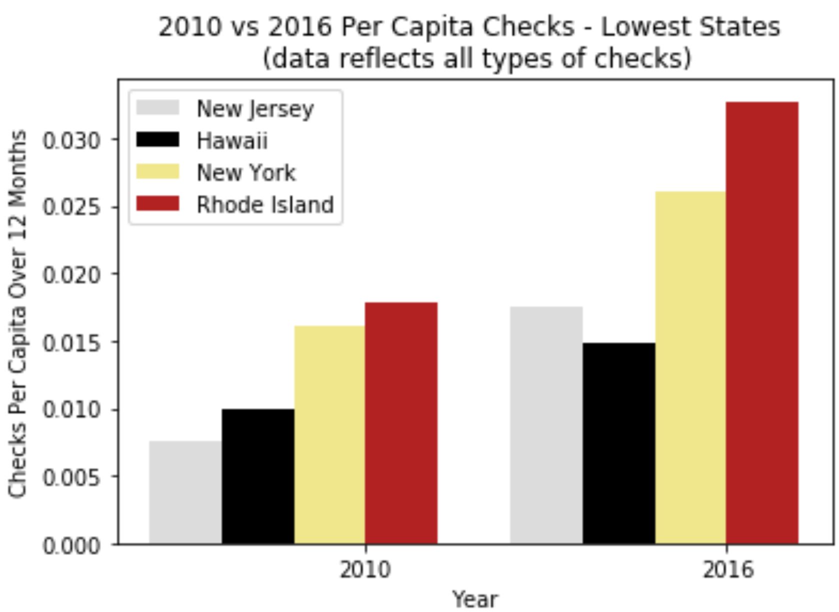
In [79]:
```
d = 2
ind = np.arange(d)
ticks = ['2010', '2016']
width = .2
large1 = [checks_2010_2016.per_capita_2010['Kentucky'], checks_2010_2016.per_capita_2016['Kentucky']]
large2 = [checks_2010_2016.per_capita_2010['Utah'], checks_2010_2016.per_capita_2016['Utah']]
large3 = [checks_2010_2016.per_capita_2010['Montana'], checks_2010_2016.per_capita_2016['Montana']]
large4 = [checks_2010_2016.per_capita_2010['Alaska'], checks_2010_2016.per_capita_2016['Alaska']]

plt.bar(ind, large1, width=width, align='edge', color='green', tick_label=ticks, label='Kentucky')
plt.bar(ind + width, large2, width=width, align='edge', color='blue', tick_label=ticks, label='Utah')
plt.bar(ind + width*2, large3, width=width, align='edge', color='cyan', tick_label=ticks, label='Montana')
plt.bar(ind + width*3, large4, width=width, align='edge', color='magenta', tick_label=ticks, label='Alaska')

plt.title('2010 vs 2016 Per Capita Checks - Highest States \n (data reflects all types of checks)' )
plt.xlabel('Year')
plt.ylabel('Checks Per Capita Over 12 Months')
plt.legend()
```

Out[79]: <matplotlib.legend.Legend at 0x11d7b6f98>



In [80]:
```
small1 = [checks_2010_2016.per_capita_2010['New Jersey'], checks_2010_
2016.per_capita_2016['New Jersey']]
small2 = [checks_2010_2016.per_capita_2010['Hawaii'], checks_2010_2016
.per_capita_2016['Hawaii']]
small3 = [checks_2010_2016.per_capita_2010['New York'], checks_2010_20
16.per_capita_2016['New York']]
small4 = [checks_2010_2016.per_capita_2010['Rhode Island'], checks_201
0_2016.per_capita_2016['Rhode Island']]

plt.bar(ind, small1, width=width, align='edge', color='gainsboro', tic
k_label=ticks, label='New Jersey')
plt.bar(ind + width, small2, width=width, align='edge', color='black',
tick_label=ticks, label='Hawaii')
plt.bar(ind + width*2, small3, width=width, align='edge', color='khaki
', tick_label=ticks, label='New York')
plt.bar(ind + width*3, small4, width=width, align='edge', color='fireb
rick', tick_label=ticks, label='Rhode Island')

plt.title('2010 vs 2016 Per Capita Checks - Lowest States \n (data ref
lects all types of checks)' )
plt.xlabel('Year')
plt.ylabel('Checks Per Capita Over 12 Months')
plt.legend()
```

Out[80]: <matplotlib.legend.Legend at 0x11d821390>



I referred to the bar chart examples in the following website for an example of how to set up bar graphs with multiple columns in matplotlib. **[http://benalexkeen.com/bar-charts-in-matplotlib/ (http://benalexkeen.com/bar-charts-in-matplotlib/)](http://benalexkeen.com/bar-charts-in-matplotlib/)**

In states that had a high number of NICS checks per capita in 2010, not all of them show growth. Some show decreases and others are relatively flat.

All of the states with low per capita figures in 2010 show increases in checks from 2010 to 2016.

Conclusions

Comments on Limitations: One major limitation to per capita section of the study is the availability of population data. Ideally we would be able to view population data each year for several years, and preferably for the same ten year period that we used to view handgun checks and total NICS checks.

Another limitation is way in which the categories in the data such as handguns and long-guns are are used by those reporting the data to the NICS. As discussed above, there appear to have been changes in certain states as to how certain types of firearms are classified. This does not impact the totals but it makes it much more difficult to analyze the individual types of checks.

In this study I often relied on total checks found in the 'totals' column. This 'totals' column aggregates different types of checks that are quite different. For example, a check for a permits is quite different from a firearm purchase. Ideally we would separate out all types of checks but some of them have very limited data and there may be some inconsistencies with how checks are classified from state to state.

One final limitation pertains to the different regulations that exists in each state. A more complete study might categorize states with similar regulations and make comparisons between those categories. This would require more than NICS data.

General Conclusion: In spite of the limitations described above, there has clearly been substantial growth in the number of background checks conducted through the NICS. This growth has occurred across nearly all states and has occurred on both an absolute basis and on a per capita basis. The growth in specific types of checks, such as checks for handguns, is harder to attribute to growth since there appears to have been changes in the way that checks have been classified, i.e. handgun vs long-gun.